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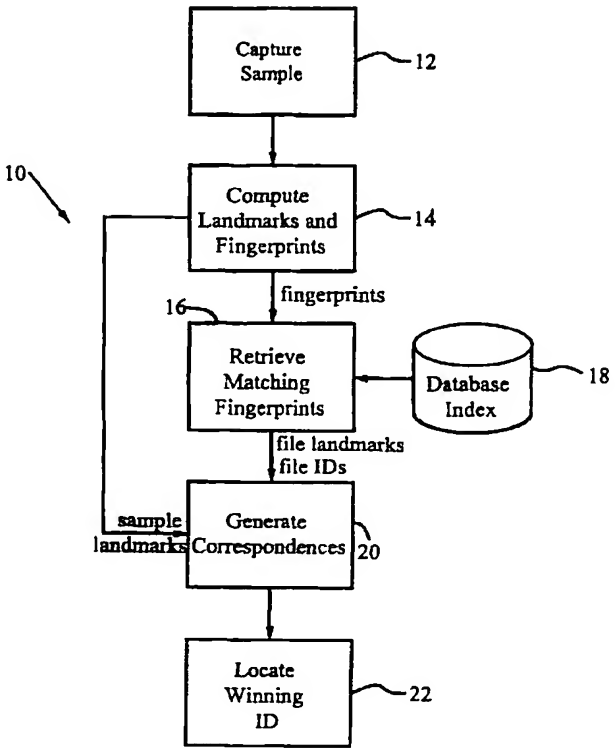

(57) Abstract: A method for recognizing an audio sample locates an audio file that most closely matches the audio sample from a database indexing a large set of original recordings. Each indexed audio file is represented in the database index by a set of landmark timepoints and associated fingerprints. Landmarks occur at reproductible locations within the file, while fingerprints represent features of the signal at or near the landmark timepoints. To perform recognition, landmarks and fingerprints are computed for the unknown sample and used to retrieve matching fingerprints from the database. For each file containing matching fingerprints, the landmarks are compared with landmarks of the sample at which the same fingerprints were computed. If a large number of corresponding landmarks are linearly related, i.e., if equivalent fingerprints of the sample and retrieved file have the same time evolution, then the file is identified with the sample. The method can be used for any type of sound or music, and is particularly effective for audio signals subject to linear and nonlinear distortion such as background noise, compression artifacts, or transmission dropouts. The sample can be identified in a time proportional to the logarithm of the number of entries in the database; given sufficient computational power, recognition can be performed in nearly real time as the sound is being sampled.

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SYSTEM AND METHODS FOR RECOGNIZING SOUND AND MUSIC SIGNALS IN HIGH NOISE AND DISTORTION

FIELD OF THE INVENTION

This invention relates generally to content-based information retrieval. More particularly, it relates to recognition of an audio signal, including sound or music, that is highly distorted or contains a high level of noise.

BACKGROUND ART

There is a growing need for automatic recognition of music or other audio signals generated from a variety of sources. For example, owners of copyrighted works or advertisers are interested in obtaining data on the frequency of broadcast of their material. Music tracking services provide playlists of major radio stations in large markets. Consumers would like to identify songs or advertising broadcast on the radio, so that they can purchase new and interesting music or other products and services. Any sort of continual or on-demand sound recognition is inefficient and labor intensive when performed by humans. An automated method of recognizing music or sound would thus provide significant benefit to consumers, artists, and a variety of industries. As the music distribution paradigm shifts from store purchases to downloading via the Internet, it is quite feasible to link directly computer-implemented music recognition with Internet purchasing and other Internet-based services.

Traditionally, recognition of songs played on the radio has been performed by matching radio stations and times at which songs were played with playlists provided either by the radio stations or from third party sources. This method is inherently limited to only radio stations for which information is available. Other methods rely on embedding inaudible codes within broadcast signals. The embedded signals are decoded at the receiver to extract identifying information about the broadcast signal. The disadvantage of this method is that special decoding devices are required to identify signals, and only those songs with embedded codes can be identified.

Any large-scale audio recognition requires some sort of content-based audio retrieval, in which an unidentified broadcast signal is compared with a database of known signals to identify similar or identical database signals. Note that content-based audio retrieval is different from existing audio retrieval by web search engines, in which only the metadata text surrounding or associated with audio files is searched. Also note that while speech recognition is useful for converting voiced signals into text that can then be indexed and

searched using well-known techniques, it is not applicable to the large majority of audio signals that contain music and sounds. In some ways, audio information retrieval is analogous to text-based information retrieval provided by search engines. In other ways, however, audio recognition is not analogous: audio signals lack easily identifiable entities such as words that provide identifiers for searching and indexing. As such, current audio retrieval schemes index audio signals by computed perceptual characteristics that represent various qualities or features of the signal.

Content-based audio retrieval is typically performed by analyzing a query signal to obtain a number of representative characteristics, and then applying a similarity measure to the derived characteristics to locate database files that are most similar to the query signal. The similarity of received objects is necessarily a reflection of the perceptual characteristics selected. A number of content-based retrieval methods are available in the art. For example, U.S. Patent No. 5,210,820, issued to Kenyon, discloses a signal recognition method in which received signals are processed and sampled to obtain signal values at each sampling point. Statistical moments of the sampled values are then computed to generate a feature vector that can be compared with identifiers of stored signals to retrieve similar signals. U.S. Patent Nos. 4,450,531 and 4,843,562, both issued to Kenyon et al., disclose similar broadcast information classification methods in which cross-correlations are computed between unidentified signals and stored reference signals.

A system for retrieving audio documents by acoustic similarity is disclosed in J. T. Foote, "Content-Based Retrieval of Music and Audio," in C.-C. J. Kuo et al., editor, *Multimedia Storage and Archiving Systems II, Proc. of SPIE*, volume 3229, pages 138-147, 1997. Feature vectors are calculated by parameterizing each audio file into mel-scaled cepstral coefficients, and a quantization tree is grown from the parameterization data. To perform a query, an unknown signal is parameterized to obtain feature vectors that are then sorted into leaf nodes of the tree. A histogram is collected for each leaf node, thereby generating an N-dimensional vector representing the unknown signal. The distance between two such vectors is indicative of the similarity between two sound files. In this method, the supervised quantization scheme learns distinguishing audio features, while ignoring unimportant variations, based on classes into which the training data are assigned by a human. Depending upon the classification system, different acoustic features are chosen to be important. Thus this method is more suited for finding similarities between songs and sorting music into classes than it is to recognizing music.

A method for content-based analysis, storage, retrieval, and segmentation of audio information is disclosed in U.S. Patent No. 5,918,223, issued to Blum et al. In this method, a number of acoustical features, such as loudness, bass, pitch, brightness, bandwidth, and Mel-frequency cepstral coefficients, are measured at periodic intervals of each file. Statistical measurements of the features are taken and combined to form a feature vector. Audio data files within a database are retrieved based on the similarity of their feature vectors to the feature vector of an unidentified file.

A key problem of all of the above prior art audio recognition methods is that they tend to fail when the signals to be recognized are subject to linear and nonlinear distortion caused by, for example, background noise, transmission errors and dropouts, interference, band-limited filtering, quantization, time-warping, and voice-quality digital compression. In prior art methods, when a distorted sound sample is processed to obtain acoustical features, only a fraction of the features derived for the original recording are found. The resulting feature vector is therefore not very similar to the feature vector of the original recording, and it is unlikely that correct recognition can be performed. There remains a need for a sound recognition system that performs well under conditions of high noise and distortion.

Another problem with prior art methods is that they are computationally intensive and do not scale well. Real-time recognition is thus not possible using prior art methods with large databases. In such systems, it is unfeasible to have a database of more than a few hundred or thousand recordings. Search time in prior art methods tends to grow linearly with the size of the database, making scaling to millions of sounds recordings economically unfeasible. The methods of Kenyon also require large banks of specialized digital signal processing hardware.

Existing commercial methods often have strict requirements for the input sample to be able to perform recognition. For example, they require the entire song or at least 30 seconds of the song to be sampled or require the song to be sampled from the beginning. They also have difficulty recognizing multiple songs mixed together in a single stream. All of these disadvantages make prior art methods unfeasible for use in many practical applications.

OBJECTS AND ADVANTAGES

Accordingly, it is a primary object of the present invention to provide a method for recognizing an audio signal subject to a high level of noise and distortion.

It is a further object of the invention to provide a recognition method that can be performed in real time based on only a few seconds of the signal to be identified.

It is another object of the invention to provide a recognition method than can recognize sounds based on samples from almost anywhere within the sound, not just at the beginning.

It is an additional object of the invention to provide a recognition method that does not require sound samples to be coded or correlated with particular radio stations or playlists.

It is a further object of the invention to provide a recognition method that can recognize each of multiple sound recordings mixed together in a single stream.

It is another object of the invention to provide a sound recognition system in which the unknown sound can be provided to the system from any environment by virtually any known method.

SUMMARY

These objects and advantages are attained by a method for recognizing a media sample, such as an audio sample, given a database index of a large number of known media files. The database index contains fingerprints representing features at particular locations of the indexed media files. The unknown media sample is identified with a media file in the database (the winning media file) whose relative locations of fingerprints most closely match the relative locations of fingerprints of the sample. In the case of audio files, the time evolution of fingerprints of the winning file matches the time evolution of fingerprints in the sample.

The method is preferably implemented in a distributed computer system and contains the following steps: determining a set of fingerprints at particular locations of the sample; locating matching fingerprints in the database index; generating correspondences between locations in the sample and locations in the file having equivalent fingerprints; and identifying media files for which a significant number of the correspondences are substantially linearly related. The file having the largest number of linearly related correspondences is deemed the winning media file. One method of identifying files with a large number of correspondences is to perform the equivalent of scanning for a diagonal line in the scatter plot generated from the pairs of correspondences. In one embodiment,

identifying the media files with a large number of linear correspondences involves searching only a first subset of the media files. Files in the first subset have a higher probability of being identified than files that are not in the first subset. The probability of identification is preferably based on empirical frequency or recency measures of previous identifications, along with *a priori* projections of identification frequency. If no media files are identified in the first subset, then the second subset, containing the remaining files, is searched. Alternatively, the files can be ranked by probability and searched in order of the ranking. The search is terminated when a file is located.

Preferably, the particular locations within the sample are reproducibly computed in dependence on the sample. Such reproducibly computable locations are called "landmarks." Fingerprints are preferably numerical values. In one embodiment, each fingerprint represents a number of features of the media sample at each location, or offset slightly from the location.

The method is particularly useful for recognizing audio samples, in which case the particular locations are timepoints within the audio sample. These timepoints occur at, for example, local maxima of spectral Lp norms of the audio sample. Fingerprints can be computed by any analysis of the audio sample, and are preferably invariant to time stretching of the sample. Examples of fingerprints include spectral slice fingerprints, multi-slice fingerprints, LPC coefficients, cepstral coefficients, and frequency components of spectrogram peaks.

The present invention also provides a system for implementing the above method, containing a landmarking object for computing the particular locations, a fingerprinting object for computing the fingerprints, a database index containing the file locations and fingerprints for the media files, and an analysis object. The analysis object implements the method by locating matching fingerprints in the database index, generating correspondences, and analyzing the correspondences to select the winning media file.

Also provided is a program storage device accessible by a computer, tangibly embodying a program of instructions executable by the computer to perform method steps for the above method.

Additionally, the invention provides a method for creating an index of a number of audio files in a database, containing the following steps: computing a set of fingerprints at particular locations of each file; and storing the fingerprints, locations, and identifiers of

the files in a memory. A corresponding fingerprint, location, and identifier is associated in the memory to form a triplet. Preferably, the locations, which can be timepoints within the audio file, are computed in dependence on the file and are reproducible. For example, the timepoints can occur at local maxima of spectral Lp norms of the audio file. In some cases, each fingerprint, which is preferably a numerical value, represents a number of features of the file near the particular location. Fingerprints can be computed from any analysis or digital signal processing of the audio file. Examples of fingerprints include spectral slice fingerprints, multi-slice fingerprints, LPC coefficients, cepstral coefficients, frequency components of spectrogram peaks, and linked spectrogram peaks.

Finally, the invention provides methods for identifying audio samples incorporating time-stretch invariant fingerprints and various hierarchical searching.

BRIEF DESCRIPTION OF THE FIGURES

Fig. **1** is a flow diagram of a method of the invention for recognizing a sound sample.

Fig. **2** is a block diagram of an exemplary distributed computer system for implementing the method of Fig. 1.

Fig. **3** is a flow diagram of a method for constructing a database index of sound files used in the method of Fig. 1.

Fig. **4** schematically illustrates landmarks and fingerprints computed for a sound sample.

Fig. **5** is a graph of L4 norms for a sound sample, illustrating the selection of landmarks.

Fig. **6** is a flow diagram of an alternative embodiment for constructing a database index of sound files used in the method of Fig. 1.

Figs. **7A-7C** show a spectrogram with salient points and linked salient points indicated.

Figs. **8A-8C** illustrate index sets, an index list, and a master index list of the method of Fig. 3.

Figs. **9A-9C** illustrate an index list, candidate list, and scatter list of the method of Fig. 1.

Figs. **10A-10B** are scatter plots illustrating correct identification and lack of identification, respectively, of an unknown sound sample.

DETAILED DESCRIPTION

The present invention provides a method for recognizing an exogenous media sample given a database containing a large number of known media files. It also provides a method for generating a database index that allows efficient searching using the recognition method of the invention. While the following discussion refers primarily to audio data, it is to be understood that the method of the present invention can be applied to any type of media samples and media files, including, but not limited to, text, audio,

video, image, and any multimedia combinations of individual media types. In the case of audio, the present invention is particularly useful for recognizing samples that contain high levels of linear and nonlinear distortion caused by, for example, background noise, transmission errors and dropouts, interference, band-limited filtering, quantization, time-warping, and voice-quality digital compression. As will be apparent from the description below, the invention works under such conditions because it can correctly recognize a distorted signal even if only a small fraction of the computed characteristics survive the distortion. Any type of audio, including sound, voice, music, or combinations of types, can be recognized by the present invention. Example audio samples include recorded music, radio broadcast programs, and advertisements.

As used herein, an exogenous media sample is a segment of media data of any size obtained from a variety of sources as described below. In order for recognition to be performed, the sample must be a rendition of part of a media file indexed in a database used by the present invention. The indexed media file can be thought of as an original recording, and the sample as a distorted and/or abridged version or rendition of the original recording. Typically, the sample corresponds to only a small portion of the indexed file. For example, recognition can be performed on a ten-second segment of a five-minute song indexed in the database. Although the term "file" is used to describe the indexed entity, the entity can be in any format for which the necessary values (described below) can be obtained. Furthermore, there is no need to store or have access to the file after the values are obtained.

A block diagram conceptually illustrating the overall steps of a method **10** of the present invention is shown in **Fig. 1.** Individual steps are described in more detail below. The method identifies a winning media file, a media file whose relative locations of characteristic fingerprints most closely match the relative locations of the same fingerprints of the exogenous sample. After an exogenous sample is captured in step **12,** landmarks and fingerprints are computed in step **14.** Landmarks occur at particular locations, e.g., timepoints, within the sample. The location within the sample of the landmarks is preferably determined by the sample itself, i.e., is dependent upon sample qualities, and is reproducible. That is, the same landmarks are computed for the same signal each time the process is repeated. For each landmark, a fingerprint characterizing one or more features of the sample at or near the landmark is obtained. The nearness of a feature to a landmark is defined by the fingerprinting method used. In some cases, a feature is considered near a landmark if it clearly corresponds to the landmark and not to a previous or subsequent landmark. In other cases, features correspond to multiple adjacent

landmarks. For example, text fingerprints can be word strings, audio fingerprints can be spectral components, and image fingerprints can be pixel RGB values. Two general embodiments of step **14** are described below, one in which landmarks and fingerprints are computed sequentially, and one in which they are computed simultaneously.

In step **16,** the sample fingerprints are used to retrieve sets of matching fingerprints stored in a database index **18,** in which the matching fingerprints are associated with landmarks and identifiers of a set of media files. The set of retrieved file identifiers and landmark values are then used to generate correspondence pairs (step **20**) containing sample landmarks (computed in step **14**) and retrieved file landmarks at which the same fingerprints were computed. The resulting correspondence pairs are then sorted by song identifier, generating sets of correspondences between sample landmarks and file landmarks for each applicable file. Each set is scanned for alignment between the file landmarks and sample landmarks. That is, linear correspondences in the pairs of landmarks are identified, and the set is scored according to the number of pairs that are linearly related. A linear correspondence occurs when a large number of corresponding sample locations and file locations can be described with substantially the same linear equation, within an allowed tolerance. For example, if the slopes of a number of equations describing a set of correspondence pairs vary by ±5%, then the entire set of correspondences is considered to be linearly related. Of course, any suitable tolerance can be selected. The identifier of the set with the highest score, i.e., with the largest number of linearly related correspondences, is the winning file identifier, which is located and returned in step **22.**

As described further below, recognition can be performed with a time component proportional to the logarithm of the number of entries in the database. Recognition can be performed in essentially real time, even with a very large database. That is, a sample can be recognized as it is being obtained, with a small time lag. The method can identify a sound based on segments of 5-10 seconds and even as low 1-3 seconds. In a preferred embodiment, the landmarking and fingerprinting analysis, step **14,** is carried out in real time as the sample is being captured in step **12.** Database queries (step **16**) are carried out as sample fingerprints become available, and the correspondence results are accumulated and periodically scanned for linear correspondences. Thus all of the method steps occur simultaneously, and not in the sequential linear fashion suggested in Fig. 1. Note that the method is in part analogous to a text search engine: a user submits a query sample, and a matching file indexed in the sound database is returned.

The method is typically implemented as software running on a computer system, with individual steps most efficiently implemented as independent software modules. Thus a system implementing the present invention can be considered to consist of a landmarking and fingerprinting object, an indexed database, and an analysis object for searching the database index, computing correspondences, and identifying the winning file. In the case of sequential landmarking and fingerprinting, the landmarking and fingerprinting object can be considered to be distinct landmarking and fingerprinting objects. Computer instruction code for the different objects is stored in a memory of one or more computers and executed by one or more computer processors. In one embodiment, the code objects are clustered together in a single computer system, such as an Intel-based personal computer or other workstation. In a preferred embodiment, the method is implemented by a networked cluster of central processing units (CPUs), in which different software objects are executed by different processors in order to distribute the computational load. Alternatively, each CPU can have a copy of all software objects, allowing for a homogeneous network of identically configured elements. In this latter configuration, each CPU has a subset of the database index and is responsible for searching its own subset of media files.

Although the invention is not limited to any particular hardware system, an example of a preferred embodiment of a distributed computer system **30** is illustrated schematically in **Fig. 2.** System **30** contains a cluster of Linux-based processors **32a-32f** connected by a multiprocessing bus architecture **34** or a networking protocol such as the Beowulf cluster computing protocol, or a mixture of the two. In such an arrangement, the database index is preferably stored in random access memory (RAM) on at least one node **32a** in the cluster, ensuring that fingerprint searching occurs very rapidly. The computational nodes corresponding to the other objects, such as landmarking nodes **32c** and **32f,** fingerprinting nodes **32b** and **32e,** and alignment scanning node **32d,** do not require as much bulk RAM as does node or nodes **32a** supporting the database index. The number of computational nodes assigned to each object may thus be scaled according to need so that no single object becomes a bottleneck. The computational network is therefore highly parallelizable and can additionally process multiple simultaneous signal recognition queries that are distributed among available computational resources. Note that this makes possible applications in which large numbers of users can request recognition and receive results in near real time.

In an alternative embodiment, certain of the functional objects are more tightly coupled together, while remaining less tightly coupled to other objects. For example, the

landmarking and fingerprinting object can reside in a physically separate location from the rest of the computational objects. One example of this is a tight association of the landmarking and fingerprinting objects with the signal capturing process. In this arrangement, the landmarking and fingerprinting object can be incorporated as additional hardware or software embedded in, for example, a mobile phone, Wireless Application Protocol (WAP) browser, personal digital assistant (PDA), or other remote terminal, such as the client end of an audio search engine. In an Internet-based audio search service, such as a content identification service, the landmarking and fingerprinting object can be incorporated into the client browser application as a linked set of software instructions or a software plug-in module such as a Microsoft dynamic link library (DLL). In these embodiments, the combined signal capture, landmarking, and fingerprinting object constitutes the client end of the service. The client end sends a feature-extracted summary of the captured signal sample containing landmark and fingerprint pairs to the server end, which performs the recognition. Sending this feature-extracted summary to the server, instead of the raw captured signal, is advantageous because the amount of data is greatly reduced, often by a factor of 500 or more. Such information can be sent in real time over a low-bandwidth side channel along with or instead of, e.g., an audio stream transmitted to the server. This enables performing the invention over public communications networks, which offer relatively small-sized bandwidths to each user.

The method will now be described in detail with reference to audio samples and audio files indexed in a sound database. The method consists of two broad components, sound database index construction and sample recognition.

Database index construction

Before sound recognition can be performed, a searchable sound database index must be constructed. As used herein, a database is any indexed collection of data, and is not limited to commercially available databases. In the database index, related elements of data are associated with one another, and individual elements can be used to retrieve associated data. The sound database index contains an index set for each file or recording in the selected collection or library of recordings, which may include speech, music, advertisements, sonar signatures, or other sounds. Each recording also has a unique identifier, `sound_ID`. The sound database itself does not necessarily store the audio files for each recording, but the `sound_IDs` can be used to retrieve the audio files from elsewhere. The sound database index is expected to be very large, containing indices for millions or even billions of files. New recordings are preferably added incrementally to the database index.

A block diagram of a preferred method **40** for constructing the searchable sound database index according to a first embodiment is shown in **Fig. 3.** In this embodiment, landmarks are first computed, and then fingerprints are computed at or near the landmarks. As will be apparent to one of average skill in the art, alternative methods may be devised for constructing the database index. In particular, many of the steps listed below are optional, but serve to generate a database index that is more efficiently searched. While searching efficiency is important for real-time sound recognition from large databases, small databases can be searched relatively quickly even if they have not been sorted optimally.

To index the sound database, each recording in the collection is subjected to a landmarking and fingerprinting analysis that generates an index set for each audio file. **Fig. 4** schematically illustrates a segment of a sound recording for which landmarks (LM) and fingerprints (FP) have been computed. Landmarks occur at specific timepoints of the sound and have values in time units offset from the beginning of the file, while fingerprints characterize the sound at or near a particular landmark. Thus, in this embodiment, each landmark for a particular file is unique, while the same fingerprint can occur numerous times within a single file or multiple files.

In step **42,** each sound recording is landmarked using methods to find distinctive and reproducible locations within the sound recording. A preferred landmarking algorithm is able to mark the same timepoints within a sound recording despite the presence of noise and other linear and nonlinear distortion. Some landmarking methods are conceptually independent of the fingerprinting process described below, but can be chosen to optimize performance of the latter. Landmarking results in a list of timepoints $\{\texttt{landmark}_k\}$ within the sound recording at which fingerprints are subsequently calculated. A good landmarking scheme marks about 5-10 landmarks per second of sound recording; of course, landmarking density depends on the amount of activity within the sound recording.

A variety of techniques are possible for computing landmarks, all of which are within the scope of the present invention. The specific technical processes used to implement the landmarking schemes of the invention are known in the art and will not be discussed in detail. A simple landmarking technique, known as Power Norm, is to calculate the instantaneous power at every possible timepoint in the recording and to select local maxima. One way of doing this is to calculate the envelope by rectifying and filtering the waveform directly. Another way is to calculate the Hilbert transform (quadrature) of the

signal and use the sum of the magnitudes squared of the Hilbert transform and the original signal.

The Power Norm method of landmarking is good at finding transients in the sound signal. The Power Norm is actually a special case of the more general Spectral Lp Norm in which p=2. The general Spectral Lp Norm is calculated at each time along the sound signal by calculating a short-time spectrum, for example via a Hanning-windowed Fast Fourier Transform (FFT). A preferred embodiment uses a samping rate of 8000Hz, an FFT frame size of 1024 samples, and a stride of 64 samples for each time slice. The Lp norm for each time slice is then calculated as the sum of the p^{th} power of the absolute values of the spectral components, optionally followed by taking the p^{th} root. As before, the landmarks are chosen as the local maxima of the resulting values over time. An example of the Spectral Lp Norm method is shown in **Fig. 5,** a graph of the L4 norm as a function of time for a particular sound signal. Dashed lines at local maxima indicate the location of the chosen landmarks.

When $p=\infty$, the $L\infty$ norm is effectively the maximum norm. That is, the value of the norm is the absolute value of the largest spectral component in the spectral slice. This norm results in robust landmarks and good overall recognition performance, and is preferred for tonal music.

Alternatively, "multi-slice" spectral landmarks can be calculated by taking the sum of p^{th} powers of absolute values of spectral components over multiple timeslices at fixed or variable offsets from each other, instead of a single slice. Finding the local maxima of this extended sum allows optimization of placement of the multi-slice fingerprints, described below.

Once the landmarks have been computed, a fingerprint is computed at each landmark timepoint in the recording in step **44.** The fingerprint is generally a value or set of values that summarizes a set of features in the recording at or near the timepoint. In a currently preferred embodiment, each fingerprint is a single numerical value that is a hashed function of multiple features. Possible types of fingerprints include spectral slice fingerprints, multi-slice fingerprints, LPC coefficients, and cepstral coefficients. Of course, any type of fingerprint that characterizes the signal or features of the signal near a landmark is within the scope of the present invention. Fingerprints can be computed by any type of digital signal processing or frequency analysis of the signal.

To generate spectral slice fingerprints, a frequency analysis is performed in the neighborhood of each landmark timepoint to extract the top several spectral peaks. A simple fingerprint value is just the single frequency value of the strongest spectral peak. The use of such a simple peak results in surprisingly good recognition in the presence of noise; however, single-frequency spectral slice fingerprints tend to generate more false positives than other fingerprinting schemes because they are not unique. The number of false positives can be reduced by using fingerprints consisting of a function of the two or three strongest spectral peaks. However, there may be a higher susceptibility to noise if the second-strongest spectral peak is not sufficiently strong enough to distinguish it from its competitors in the presence of noise. That is, the calculated fingerprint value may not be sufficiently robust to be reliably reproducible. Despite this, the performance of this case is also good.

In order to take advantage of the time evolution of many sounds, a set of timeslices is determined by adding a set of time offsets to a landmark timepoint. At each resulting timeslice, a spectral slice fingerprint is calculated. The resulting set of fingerprint information is then combined to form one multitone or multi-slice fingerprint. Each multi-slice fingerprint is much more unique than the single spectral slice fingerprint, because it tracks temporal evolution, resulting in fewer false matches in the database index search described below. Experiments indicate that because of their increased uniqueness, multi-slice fingerprints computed from the single strongest spectral peak in each of two timeslices result in much faster computation (about 100 times faster) in the subsequent database index search, but with some degradation in recognition percentage in the presence of significant noise.

Alternatively, instead of using a fixed offset or offsets from a given timeslice to calculate a multi-slice fingerprint, variable offsets can be used. The variable offset to the chosen slice is the offset to the next landmark, or a landmark in a certain offset range from the "anchor" landmark for the fingerprint. In this case, the time difference between the landmarks is also encoded into the fingerprint, along with multi-frequency information. By adding more dimensions to the fingerprints, they become more unique and have a lower chance of false match.

In addition to spectral components, other spectral features can be extracted and used as fingerprints. Linear predictive coding (LPC) analysis extracts the linearly predictable features of a signal, such as spectral peaks, as well as spectral shape. LPC is well known in the art of digital signal processing. For the present invention, LPC coefficients of

waveform slices anchored at landmark positions can be used as fingerprints by hashing the quantized LPC coefficients into an index value.

Cepstral coefficents are useful as a measure of periodicity and can be used to characterize signals that are harmonic, such as voices or many musical instruments. Cepstral analysis is well known in the art of digital signal processing. For the present invention, a number of cepstral coefficients are hashed together into an index and used as a fingerprint.

An alternative embodiment **50,** in which landmarks and fingerprints are computed simultaneously, is shown in **Fig. 6.** Steps **42** and **44** of Fig. 3 are replaced by steps **52, 54,** and **56.** As described below, a multidimensional function is computed from the sound recording in step **52,** and landmarks (**54**) and fingerprints (**56**) are extracted from the function.

In one implementation of the embodiment of Fig. 6, landmarks and fingerprints are computed from a spectrogram of the sound recording. A spectrogram is a time-frequency analysis of a sound recording in which windowed and overlapped frames of sound samples are spectrally analyzed, typically using a Fast Fourier Transform (FFT). As before, a preferred embodiment uses a samping rate of 8000Hz, an FFT frame size of 1024 samples, and a stride of 64 samples for each time slice. An example of a spectrogram is shown in **Fig. 7A.** Time is on the horizontal axis, and frequency is on the vertical axis. Each sequential FFT frame is stacked vertically at corresponding evenly-spaced intervals along the time axis. A spectrogram plot depicts the energy density at each time-frequency point; darker areas on the plot represent higher energy density. Spectrograms are well-known in the art of audio signal processing. For the present invention, landmarks and fingerprints can be obtained from salient points such as local maxima of the spectrogram, circled in the spectrogram of **Fig. 7B.** For example, time and frequency coordinates of each peak are obtained, the time taken to be the landmark, and the frequency used to compute the corresponding fingerprint. This spectrogram peak landmark is similar to the $L\infty$ norm, in which the maximum absolute value of the norm determines the landmark location. In the spectrogram, however, the local maximum search is taken over patches of the time-frequency plane, rather than over an entire timeslice.

In this context, the set of salient points resulting from the point extraction analysis of a sound recording is referred to as a constellation. For a constellation consisting of local maxima, a preferred analysis is to select points that are energy maxima of the time-

frequency plane over a neighborhood around each selected point. For example, a point at coordinate (t_o, f_o) is selected if it is the maximum-energy point within a rectangle with corners (t_o-T, f_o-F), (t_o-T, f_o+F), (t_o+T, f_o-F), and (t_o+T, f_o+F), i.e., a rectangle with sides of length $2T$ and $2F$, with T and F chosen to provide a suitable number of constellation points. The bounds of the rectangle can also vary in size according to frequency value. Of course, any region shape can be used. The maximum-energy criterion can also be weighted such that a competing time-frequency energy peak is inversely weighted according to a distance metric in the time-frequency plane, i.e., more distant points have lower weighting. For example, the energy can be weighted as

$$\frac{S(t,f)}{1+C_t(t-t_o)^2+C_f(f-f_o)^2},$$

where $S(t,f)$ is the magnitude squared value of the spectrogram at point (t,f), and C_t and C_f are positive values (not necessarily constants). Other distance-weighting functions are possible. Local maxima selection constraints can be applied to other (non-maximum) salient point feature extraction schemes, and are within the scope of the invention.

This method results in pairs of values that are very similar to the single-frequency spectral fingerprint described above, with many of the same properties. The spectrogram time-frequency method generates more landmark/fingerprint pairs than the single-frequency method, but can also yield many false matches in the matching stage described below. However, it provides more robust landmarking and fingerprinting than the single-frequency spectral fingerprint, because dominant noise in the sound sample may not extend to all parts of the spectrum in each slice. That is, there are most likely some landmark and fingerprint pairs in parts of the spectrum that are not affected by the dominant noise.

This spectrogram landmarking and fingerprinting method is a special case of feature analysis methods that compute a multidimensional function of the sound signal, in which one of the dimensions is time, and locate salient points in the function values. Salient points can be local maxima, local minima, zero crossings, or other distinctive features. The landmarks are taken to be the time coordinates of the salient points, and the corresponding fingerprints are computed from at least one of the remaining coordinates. For example, the non-time coordinate(s) of the multidimensional salient point can be hashed together to form a multidimensional functional fingerprint.

The variable offset method described above for multi-slice spectral fingerprints can be applied to spectrogram or other multidimensional function fingerprints. In this case, points in a constellation are linked together to form linked points, as illustrated in the spectrogram shown in **Fig. 7C.** Each point in the constellation serves as an anchor point defining the landmark time, and the remaining coordinate values of the other points are combined to form the linked fingerprint. Points that are near each other, for example, as defined below, are linked together to form more complex aggregate feature fingerprints that may be more easily distinguished and searched. As with the multi-slice spectral fingerprints, the goal of combining information from multiple linked salient points into a single fingerprint is to create more diversity of possible fingerprint values, thereby decreasing the probability of false match, i.e., decreasing the probability that the same fingerprint describes two different music samples.

In principle, each of N salient points can be linked to each other point in a two-point linkage scheme, producing about $N^2/2$ combinations. Similarly, for a K-point linkage, the number of possible combinations resulting from a constellation is of order N^K. In order to avoid such a combinatorial explosion, it is desirable to constrain the neighborhood of points that are linked together. One way to accomplish such a constraint is to define a "target zone" for each anchor point. An anchor point is then linked with points in its target zone. It is possible to select a subset of points within the target zone to link to—not every point needs to be linked. For example, just the points associated with the strongest peaks in the target zone can be linked. A target zone can have a fixed shape or vary according to characteristics of the anchor point. A simple example of a target zone of an anchor point (t_0,f_0) for a spectrogram peak constellation is the set of points (t,f) in the spectrogram strip such that t is in the interval $[t_0+L, t_0+L+W]$, where L is the lead into the future and W is the width of the target zone. In this scheme, all frequencies are allowed in the target zone. L or W can be variable, for example, if a rate control mechanism is used to modulate the number of linkage combinations being produced. Alternatively, frequency restrictions can be implemented, for example, by constraining the target zone such that the frequency f is in the interval $[f_o-F, f_o+F]$, where F is a bounding parameter. An advantage of a frequency constraint is that in psychoacoustics, it is known that melodies tend to cohere better when sequences of notes have frequencies that are near each other. Such a constraint may enable more "psychoacoustically realistic" recognition performance, although modeling psychoacoustics is not necessarily a goal of this invention. It is also possible to consider the opposite rule, in which f is chosen outside of the region $[f_o-F, f_o+F]$. This forces the linkage of points that are different from each other in frequency, possibly avoiding cases in which constellation extraction artifacts produce

stuttering sequences of time-frequency points that are close in time and have the same frequency. As with other locality parameters, F is not necessarily constant and can, for example, be a function of f_o.

When including time coordinates of non-anchor salient points in fingerprint values, relative time values must be used to allow the fingerprints to be time invariant. For example, the fingerprint can be a function of (i) non-time coordinate values and/or (ii) difference(s) of the corresponding time coordinate values of the salient points. The time difference(s) can be taken, for example, with respect to the anchor point or as successive differences between sequential salient points in the linked set. The coordinate and difference values can be packed into concatenated bit fields to form the hashed fingerprint. As will be apparent to one of average skill in the art, many other ways of mapping sets of coordinate values into a fingerprint value exist and are within the scope of the present invention.

A concrete instantiation of this scheme uses $N>1$ linked spectrogram peaks with coordinates (t_k, f_k), $k=1,..,N$. Then, (i) the time t_1 of the first peak is taken as the landmark time, and (ii) the time differences $\Delta t_k = t_k - t_1$, $k=2,..,N$, plus the frequencies f_k, $k=1,..,N$, of the linked peaks are hashed together to form a fingerprint value. The fingerprint can be computed from all or from a subset of all available Δt_k and f_k coordinates. For example, some or all of the time difference coordinates can be omitted if desired.

Another advantage of using multiple points to form the fingerprint is that the fingerprint encoding can be made invariant with respect to time stretching, e.g., when a sound recording is played back at a speed different than the original recording speed. This advantage applies to both the spectrogram and the timeslice methods. Note that in a stretched time signal, time differences and frequency have a reciprocal relationship (e.g., decreasing the time difference between two points by a factor of two doubles the frequency). This method takes advantage of that fact by combining time differences and frequencies in a way that removes the time stretching from the fingerprint.

For example, in an N-point spectrogram peak case with coordinate values (t_k, f_k), $k=1,..,N$, the available intermediate values to hash into a fingerprint are $\Delta t_k = t_k - t_1$, $k=2,..,N$, and f_k, $k=1,..,N$. The intermediate values can then be made invariant with respect to time-stretching by taking one of the frequencies as a reference frequency, say f_1, and forming (i) quotients with the remaining frequencies and (ii) products with the time differences.

For example, intermediate values can be $g_k = f_k/f_1$, $k=2,..,N$, and $s_k = \Delta t_k f_1$, $k=2,..,N$. If the sample is sped up by a factor of α, then the frequency f_k becomes αf_k and the time difference Δt_k becomes $\Delta t_k/\alpha$, so that $g_k = \alpha f_k/\alpha f_1 = f_k/f_1$, and $s_k = (\Delta t_k/\alpha)(\alpha f_1) = \Delta t_k f_1$. These new intermediate values are then combined using a function to form a hashed fingerprint value that is independent of time stretching. For example, the g_k and s_k values may be hashed by packing them into concatenated bitfields.

Alternatively, instead of a reference frequency, a reference time difference may be used, e.g., Δt_2. In this case, the new intermediate values are calculated as the (i) quotients $\Delta t_k/\Delta t_2$ with the remaining time differences and (ii) products $\Delta t_2 f_k$ with the frequencies. This case is equivalent to using a reference frequency, because the resulting values can be formed from products and quotients of the g_k and s_k values above. Reciprocals of the frequency ratios can be used equally effectively; sums and differences of logarithmic values of the original intermediate values can also be substituted for products and differences, respectively. Any time-stretch-independent fingerprint value obtained by such commutations, substitutions, and permutations of mathematical operations is within the scope of the invention. Additionally, multiple reference frequencies or reference time differences, which also relativize time differences, can be used. The use of multiple reference frequencies or reference time differences is equivalent to the use of a single reference, because the same result can be achieved by arithmetic manipulation of the g_k and s_k values.

Returning to Figs. 3 and 6, landmarking and fingerprinting analyses by any of the above methods result in an index set for each `Sound_ID`, as shown in **Fig. 8A.** An **index set** for a given sound recording is a list of pairs of values (`fingerprint, landmark`). Each indexed recording typically has on the order of one thousand (`fingerprint, landmark`) pairs in its index set. In the first embodiment described above, in which the landmarking and fingerprinting techniques are essentially independent, they can be treated as separate and interchangeable modules. Depending upon the system, signal quality, or type of sound to be recognized, one of a number of different landmarking or fingerprinting modules can be employed. In fact, because the index set is composed simply of pairs of values, it is possible and often preferable to use multiple landmarking and fingerprinting schemes simultaneously. For example, one landmarking and fingerprinting scheme may be good at detecting unique tonal patterns, but poor at identifying percussion, whereas a different algorithm may have the opposite attributes. The use of multiple landmarking/fingerprinting strategies results in a more robust and richer range of recognition performance. Different fingerprinting techniques can be used

together by reserving certain ranges of fingerprint values for certain kinds of fingerprints. For example, in a 32-bit fingerprint value, the first 3 bits can be used to specify which of 8 fingerprinting schemes the following 29 bits are encoding.

After index sets are generated for each sound recording to be indexed in the sound database, a searchable database index is constructed in such a way as to allow fast (i.e., log time) searching. This is accomplished in step **46** by constructing a list of triplets (`fingerprint, landmark, sound_ID`), obtained by appending the corresponding `sound_ID` to each doublet within each index set. All such triplets for all sound recordings are collected into a large **index list**, an example of which is shown in **Fig. 8B.** In order to optimize the subsequent search process, the list of triplets is then sorted according to fingerprint. Fast sorting algorithms are well known in the art and extensively discussed in D.E. Knuth, *The Art of Computer Programming, Volume 3: Sorting and Searching*, Reading, Massachusetts: Addison-Wesley, 1998, herein incorporated by reference. High-performance sorting algorithms can be used to sort the list in $N \log N$ time, where N is the number of entries in the list.

Once the index list is sorted, it is further processed in step **48** by segmenting such that each unique fingerprint in the list is collected into a new **master index list,** an example of which is shown in **Fig. 8C.** Each entry in the master index list contains a fingerprint value and a pointer to a list of (`landmark,sound_ID`) pairs. Depending upon the number and character of recordings indexed, a given fingerprint can appear hundreds of times or more within the entire collection. Rearranging the index list into a master index list is optional but saves memory, because each fingerprint value appears only once. It also speeds up the subsequent database search, since the effective number of entries in the list is greatly reduced to a list of unique values. Alternatively, the master index list can be constructed by inserting each triplet into a B-tree. Other possibilities exist for constructing the master index list, as known to those of average skill in the art. The master index list is preferably held in system memory, such as DRAM, for fast access during signal recognition. The master index list can be held in the memory of a single node within the system, as illustrated in Fig. 2. Alternatively, the master index list can be broken up into pieces distributed among multiple computational nodes. Preferably, the sound database index referred to above is the master index list illustrated in Fig. 8C.

The sound database index is preferably constructed offline and updated incrementally as new sounds are incorporated into the recognition system. To update the list, new fingerprints can be inserted into the appropriate location in the master list. If new

recordings contain existing fingerprints, the corresponding (`landmark,sound_ID`) pairs are added to the existing lists for those fingerprints.

Recognition system

Using the master index list generated as described above, sound recognition is performed on an exogenous sound sample, typically supplied by a user interested in identifying the sample. For example, the user hears a new song on the radio and would like to know the artist and title of the song. The sample can originate from any type of environment, such as a radio broadcast, disco, pub, submarine, sound file, segment of streaming audio, or stereo system, and may contain background noise, dropouts, or talking voices. The user may store the audio sample in a storage device such as an answering machine, computer file, tape recorder, or telephone or mobile phone voicemail system before providing it to the system for recognition. Based on system setup and user constraints, the audio sample is provided to the recognition system of the present invention from any number of analog or digital sources, such as a stereo system, television, compact disc player, radio broadcast, answering machine, telephone, mobile telephone, Internet streaming broadcast, FTP, computer file as an email attachment, or any other suitable means of transmitting such recorded material. Depending on the source, the sample can be in the form of acoustic waves, radio waves, a digital audio PCM stream, a compressed digital audio stream (such as Dolby Digital or MP3), or an Internet streaming broadcast. A user interacts with the recognition system through a standard interface such as a telephone, mobile telephone, web browser, or email. The sample can be captured by the system and processed in real time, or it can be reproduced for processing from a previously captured sound (e.g., a sound file). During capture, the audio sample is sampled digitally and sent to the system by a sampling device such as a microphone. Depending upon the capture method, the sample is likely subjected to further degradation due to limitations of the channel or sound capture device.

Once the sound signal has been converted into digital form, it is processed for recognition. As with the construction of index sets for database files, landmarks and fingerprints are calculated for the sample using the same algorithm that was used for processing the sound recording database. The method works optimally if the processing of a highly distorted rendition of an original sound file yields the identical or similar set of landmark and fingerprint pairs as was obtained for the original recording. The resulting index set for the sound sample is a set of pairs of analyzed values, (`fingerprint,landmark`), shown in **Fig. 9A.**

Given the pairs for the sound sample, the database index is searched to locate potentially matching files. Searching is carried out as follows: each $(\texttt{fingerprint}_k, \texttt{landmark}_k)$ pair in the index set of the unknown sample is processed by searching for $\texttt{fingerprint}_k$ in the master index list. Fast searching algorithms on an ordered list are well known in the art and extensively discussed in D.E. Knuth, *The Art of Computer Programming, Volume 3: Sorting and Searching*, Reading, Massachusetts: Addison-Wesley, 1998. If $\texttt{fingerprint}_k$ is found in the master index list, then its corresponding list of matching $(\texttt{landmark}^*_j, \texttt{sound_ID}_j)$ pairs is copied and augmented with $\texttt{landmark}_k$ to form a set of triplets of the form $(\texttt{landmark}_k, \texttt{landmark}^*_j, \texttt{sound_ID}_j)$. In this notation, an asterisk (*) indicates a landmark of one of the indexed files in the database, while a landmark without an asterisk refers to the sample. In some cases, it is preferable that the matching fingerprints are not necessarily identical, but are similar; for example, they may differ by within a previously determined threshold. Matching fingerprints, whether identical or similar, are referred to as equivalent. The $\texttt{sound_ID}_j$ in the triplet corresponds to the file having the asterisked landmark. Thus each triplet contains two distinct landmarks, one in the database index and one in the sample, at which equivalent fingerprints were computed. This process is repeated for all *k* ranging over the input sample index set. All resulting triplets are collected into a large **candidate list,** illustrated in **Fig. 9B.** The candidate list is so called because it contains the sound_IDs of sound files that, by virtue of their matching fingerprints, are candidates for identification with the exogenous sound sample.

After the candidate list is compiled, it is further processed by segmenting according to sound_ID. A convenient way of doing this is to sort the candidate list by sound_ID or to insert it into a B-tree. A large number of sorting algorithms are available in the art, as discussed above. The result of this process is a list of candidate sound_IDs, each of which has a **scatter list** of pairs of sample and file landmark timepoints with the sound_ID optionally stripped off, $(\texttt{landmark}_k, \texttt{landmark}^*_j)$, as shown in **Fig. 9C.** Each scatter list thus contains a set of corresponding landmarks, corresponding by virtue of their being characterized by equivalent fingerprint value.

The scatter list for each candidate sound_ID is then analyzed to determine whether the sound_ID is a match for the sample. An optional thresholding step can be used first to eliminate a potentially large number of candidates that have very small scatter lists. Clearly, candidates having only one entry in their scatter lists, i.e., only one fingerprint in

common with the sample, do not match the sample. Any suitable threshold number greater than or equal to one can be used.

Once the final number of candidates is determined, the winning candidate is located. If the following algorithm does not locate a winning candidate, then a failure message is returned. A key insight into the matching process is that the time evolution in matching sounds must follow a linear correspondence, assuming that the timebases on both sides are steady. This is almost always true unless one of the sounds has been nonlinearly warped intentionally or subject to defective playback equipment such as a tape deck with a warbling speed problem. Thus, the correct landmark pairs ($\texttt{landmark}_n$, $\texttt{landmark}^*_n$) in the scatter list of a given `sound_ID` must have a linear correspondence of the form

$$\texttt{landmark}^*_n = m*\texttt{landmark}_n + \texttt{offset},$$

where m is the slope, which should be near one; $\texttt{landmark}_n$ is the timepoint within the exogenous sample; $\texttt{landmark}^*_n$ is the corresponding timepoint within the sound recording indexed by `sound_ID`; and `offset` is the time offset into the sound recording corresponding to the beginning of the exogenous sound sample. Landmark pairs that can be fit with the above equation for particular values of m and `offset` are said to be linearly related. Obviously, the concept of being linearly related is only valid for more than one pair of corresponding landmarks. Note that this linear relationship identifies the correct sound file with high probability, while excluding outlying landmark pairs that have no significance. While it is possible for two distinct signals to contain a number of identical fingerprints, it is very unlikely that these fingerprints have the same relative time evolutions. The requirement for linear correspondences is a key feature of the present invention, and provides significantly better recognition than techniques that simply count the total number of features in common or measure the similarity between features. In fact, because of this aspect of the invention, sounds can be recognized even if fewer than 1% of the original recording's fingerprints appear in the exogenous sound sample, i.e., if the sound sample is very short or if it is significantly distorted.

The problem of determining whether there is a match for the exogenous sample is thus reduced to the equivalent of finding a diagonal line with slope near one within a scatter plot of the landmark points of a given scatter list. Two sample scatter plots are shown in **Figs. 10A** and **10B,** with sound file landmarks on the horizontal axis and exogenous sound sample landmarks on the vertical axis. In **Fig. 10A,** a diagonal line of slope approximately equal to one is identified, indicating that the song indeed matches the

sample, i.e., that the sound file is a winning file. The intercept at the horizontal axis indicates the offset into the audio file at which the sample begins. No statistically significant diagonal line is found in the scatter plot of **Fig. 10B,** indicating that the sound file is not a match for the exogenous sample.

There are many ways of finding a diagonal line in a scatter plot, all of which are within the scope of the present invention. It is to be understood that the phrase "locating a diagonal line" refers to all methods that are equivalent to locating a diagonal line without explicitly producing a diagonal line. A preferred method starts by subtracting $m*landmark_n$ from both sides of the above equation to yield

$$(landmark^*_n - m*landmark_n) = offset.$$

Assuming that m is approximately equal to one, i.e., assuming no time stretching, we arrive at

$$(landmark^*_n - landmark_n) = offset.$$

The diagonal-finding problem is then reduced to finding multiple landmark pairs for a given `sound_ID` that cluster near the same `offset` value. This can be accomplished easily by subtracting one landmark from the other and collecting a histogram of the resulting offset values. The histogram can be prepared by sorting the resulting offset values using a fast sort algorithm or by creating bin entries with counters and inserting into a B-tree. The winning offset bin in the histogram contains the highest number of points. This bin is referred to herein as the peak of the histogram. Since the offset must be positive if the exogenous sound signal is fully contained within the correct library sound file, landmark pairs that result in a negative offset can be excluded. Similarly, offsets beyond the end of the file can also be excluded. The number of points in the winning offset bin of the histogram is noted for each qualifying `sound_ID`. This number becomes the score for each sound recording. The sound recording in the candidate list with the highest score is chosen as the winner. The winning `sound_ID` is reported to a user as described below to signal the success of the identification. To prevent false identification, a minimum threshold score can be used to gate the success of the identification process. If no library sound has a score exceeding the threshold, then there is no recognition, and the user is so informed.

If the exogenous sound signal contains multiple sounds, then each individual sound can be recognized. In this case, multiple winners are located in the alignment scan. It is not necessary to know that the sound signal contains multiple winners, because the alignment scan will locate more than one `sound_ID` with a score that is much higher than the remaining scores. The fingerprinting method used preferably exhibits good linear superposition, so that the individual fingerprints can be extracted. For example, a spectrogram fingerprinting method exhibits linear superposition.

If the sound sample has been subjected to time stretching, then the slope is not identically equal to one. The result of assuming a unity slope on a time stretched sample (assuming that the fingerprints are time stretch invariant) is that the computed offset values are not equal. One way to address this and to accommodate moderate time stretching is to increase the size of the offset bins, i.e., to consider a range of offsets to be equal. In general, if the points do not fall on a straight line, then the computed offset values are significantly different, and a slight increase in the size of the offset bins does not yield a significant number of false positives.

Other line-finding strategies are possible. For example, a Radon or Hough transform, described in T. Risse, "Hough Transform for Line Recognition," *Computer Vision and Image Processing*, 46, 327-345, 1989, which are well known in the arts of machine vision and graphics research, may be used. In the Hough transform, each point of the scatter plot projects to a line in (slope, offset) space. The set of points in the scatter plot are thus projected onto the dual space of lines in the Hough transform. Peaks in the Hough transform correspond to intersections of the parameter lines. The global peak of such a transform of a given scatter plot indicates the most number of intersecting lines in the Hough transform, and thus the most number of co-linear points. To allow a speed variation of 5%, for example, the construction of the Hough transform can be restricted to the region where the slope parameter varies between 0.95 and 1.05, thus saving some computational effort.

Hierarchical search

In addition to the thresholding step that eliminates candidates with very small scatter lists, further improvements in efficiency can be made. In one such improvement, the database index is segmented into at least two parts according to probability of occurrence, and only the sound files with the highest probability of matching the sample are initially searched. The division can occur at various stages of the process. For example, the master index list (Fig. 8C) can be segmented into two or more parts such that steps **16** and **20** are first

performed on one of the segments. That is, files corresponding to matching fingerprints are retrieved from only a fraction of the database index, and a scatter list is generated from this fraction. If a winning sound file is not located, then the process is repeated on the remainder of the database index. In another implementation, all files are retrieved from the database index, but the diagonal line scan is performed separately on the different segments.

Using this technique, the diagonal line scan, a computationally intensive part of the method, is performed first on a small subset of the sound files in the database index. Because the diagonal line scan has a time component that is approximately linear with respect to the number of sound files being scanned, performing such a hierarchical search is highly advantageous. For example, assume that the sound database index contains fingerprints representing 1,000,000 sound files, but that only about 1000 files match the sample queries with high frequency, e.g., 95% of the queries are for 1000 files, while only 5% of the queries are for the remaining 999,000 files. Assuming a linear dependence of computational cost on the number of files, the cost is proportional to 1000 95% of the time and proportional to 999,000 only 5% of the time. The average cost is therefore proportional to about 50,900. A hierarchical search thus yields about a factor of 20 savings in computational load. Of course, the database index can be segmented into more than two levels of hierarchy, e.g., a group of new releases, a group of recently released songs, and a group of older, less popular songs.

As described above, the search is first performed on a first subset of sound files, the high-probability files, and then, only if the first search fails, performed on a second subset containing the remaining files. Failure of the diagonal line scan occurs if the number of points in each offset bin does not reach a predetermined threshold value. Alternatively, the two searches can be carried out in parallel (simultaneously). If the correct sound file is located in a search of the first subset, then a signal is sent to terminate the search of the second subset. If the correct sound file is not located in the first search, then the second search continues until a winning file is located. These two different implementations involve tradeoffs in computational effort and time. The first implementation is more computationally efficient, but introduces a slight latency if the first search fails, while the second implementation wastes computational effort if the winning file is in the first subset but minimizes latency if it is not.

The object of segmenting the list is to estimate the probability that a sound file is the target of a query and to limit the search to those files most likely to match the query

sample. There are various possible ways of assigning probabilities and sorting the sounds in the database, all of which are within the scope of the present invention. Preferably, probabilities are assigned based on recency or frequency of being identified as the winning sound file. Recency is a useful measure, particularly for popular songs, because musical interests change quite rapidly over time as new songs are released. After the probability scores are computed, rankings are assigned to the files, and the list self-sorts by the ranking. The sorted list is then segmented into two or more subsets for searching. The smaller subset can contain a predetermined number of files. For example, if the ranking locates a file within the top, say, 1000 files, then the file is placed in the smaller, faster search. Alternatively, the cut-off points for the two subsets can be adjusted dynamically. For example, all files with a score exceeding a particular threshold value can be placed within the first subset, and so the number of files in each subset changes continually.

One particular way of computing the probability is to increment a sound file's score by one each time it is identified as a match for the query sample. To take recency into account, all of the scores are reduced downward periodically, so that newer queries have a stronger effect on the ranking than do older queries. For example, all scores can be ratcheted downward by a constant multiplicative factor upon each query, resulting in an exponential decay of the score if not updated. Depending upon the number of files in the database, which can easily be one million, this method can require updating a large number of scores at every query, making it potentially undesirable. Alternatively, the scores can be adjusted downward at relatively infrequent intervals, such as once per day. The ordering resulting from less frequent adjustment is effectively similar, but not quite identical, to the ordering resulting from adjustment with each query. However, the computational load to update the rankings is much lower.

A slight variation of this recency adjustment, which more exactly preserves the recency score, is to add an exponentially growing score update a^t to the winning sound file upon query, where t is the amount of time elapsed since the last global update. All scores are then adjusted downward by dividing by a^T at each global update, where T is the total elapsed time since the last global update. In this variation, a is a recency factor that is greater than one.

In addition to the ranking described above, some *a priori* knowledge can be introduced to help seed the listing. For example, new releases are likely to have higher numbers of queries than older songs. Thus, new releases can be placed automatically in the first

subset containing songs with a higher probability of matching queries. This can be performed independently of the self-ranking algorithm described above. If the self-ranking feature is also used, new releases can be assigned initial rankings that place them somewhere within the first subset. The new releases can be seeded at the very top of the list, at the bottom of the list of high probability songs, or somewhere in between. For the purposes of the search, the initial location does not matter, because the ranking converges over time to reflect the true level of interest.

In an alternative embodiment, the search is performed in the order of the recency rankings and is terminated when a `sound_ID` score exceeds a predetermined threshold value. This is equivalent to the above method in which each segment contains one `sound_ID` only. Experiments show that the score of a winning sound is much higher than scores of all other sound files, and so a suitable threshold can be chosen with minimal experimentation. One way to implement this embodiment is to rank all `sound_IDs` in the database index according to recency, with arbitrary tie-breaking in the case of identical scores. Because each recency ranking is unique, there is a one-to-one mapping between the recency score and the `sound_ID`. The ranking can then be used instead of the `sound_ID` when sorting by `sound_ID` to form the list of candidate `Sound_IDs` and associated scatter lists (Fig. 9C). The ranking numbers can be bound to the index when the index list of triplets (`fingerprint, landmark, sound_ID`) is generated and before the index list is sorted into the master index list. The ranking then takes the place of the `sound_ID`. Alternatively, a search and replace function can be used to replace the `sound_ID` with the ranking. As rankings are updated, new rankings are mapped onto the old rankings, provided that the mapping integrity is maintained.

Alternatively, the rankings can be bound later in the process. Once the scatter lists are created, a ranking can be associated with each `sound_ID`. The sets are then sorted by ranking. In this implementation, only the pointers to the scatter lists need to be modified; the grouping into scatter lists does not need to be repeated. The advantage of later bindings is that the entire database index does not need to be recreated each time the rankings are updated.

Note that the popularity ranking may itself be of interest as an object of economic value. That is, the ranking reflects the desirability of consumers to obtain an identification of an unknown sound sample. In many cases, the query is prompted by a desire to purchase a recording of the song. In fact, if demographic information about the user is known, then alternative ranking schemes can be implemented for each desired demographic group. A

user's demographic group can be obtained from profile information requested when the user signs up for the recognition service. It can also be determined dynamically by standard collaborative filtering techniques.

In a real-time system, the sound is provided to the recognition system incrementally over time, enabling pipelined recognition. In this case, it is possible to process the incoming data in segments and to update the sample index set incrementally. After each update period, the newly augmented index set is used to retrieve candidate library sound recordings using the searching and scanning steps above. The database index is searched for fingerprints matching newly obtained sample fingerprints, and new ($\texttt{landmark}_k$, $\texttt{landmark}^*_j$, $\texttt{sound_ID}_j$) triplets are generated. New pairs are added to the scatter lists, and the histograms are augmented. The advantage of this approach is that if sufficient data has been collected to identify the sound recording unambiguously, e.g., if the number of points in an offset bin of one of the sound files exceeds a high threshold or exceeds the next highest sound file score, then data acquisition can be terminated and the result announced.

Once the correct sound has been identified, the result is reported to a user or system by any suitable method. For example, the result can be reported by a computer printout, email, web search result page, SMS (short messaging service) text messaging to a mobile phone, computer-generated voice annotation over a telephone, or posting of the result to a web site or Internet account that the user can access later. The reported results can include identifying information of the sound such as the name and artist of a song; the composer, name, and recording attributes (e.g., performers, conductor, venue) of a classical piece; the company and product of an advertisement; or any other suitable identifiers. Additionally, biographical information, information about concerts in the vicinity, and other information of interest to fans can be provided; hyperlinks to such data may be provided. Reported results can also include the absolute score of the sound file or its score in comparison to the next highest scored file.

One useful outcome of the recognition method is that it does not confuse two different renditions of the same sound. For example, different performances of the same piece of classical music are not considered to be the same, even if a human cannot detect a difference between the two. This is because it is highly unlikely that the landmark/fingerprint pairs and their time evolution exactly match for two different performances. In a current embodiment, the landmark/fingerprint pairs must be within about 10 ms of one another for a linear correspondence to be identified. As a result, the

automatic recognition performed by the present invention makes it possible for the proper performance/soundtrack and artist/label to be credited in all cases.

Example implementation

A preferred implementation of the invention, continuous sliding window audio recognition, is described below. A microphone or other source of sound is continually sampled into a buffer to obtain a record of the previous N seconds of sound. The contents of the sound buffer are periodically analyzed to ascertain the identity of the sound content. The sound buffer can have a fixed size or it can grow in size as the sound is sampled, referred to herein as sequentially growing segments of the audio sample. A report is made to indicate the presence of identified sound recordings. For example, a log file can be collected, or a display can be shown on a device indicating information about the music, such as title, artist, album cover art, lyrics, or purchase information. To avoid redundancy, a report can be made only when the identity of recognized sound changes, for example, after a program change on a jukebox. Such a device can be used to create a list of music played from any sound stream (radio, internet streaming radio, hidden microphone, telephone call, etc.). In addition to the music identity, information such as the time of recognition can be logged. If location information is available (e.g., from GPS), such information can also be logged.

To accomplish the identification, each buffer can be identified *de novo*. Alternatively, sound parameters can be extracted, for example, into fingerprints or other intermediate feature-extracted forms, and stored in a second buffer. New fingerprints can be added to the front of the second buffer, with old fingerprints being discarded from the end of the buffer. The advantage of such a rolling buffer scheme is that the same analysis does not need to be performed redundantly on old overlapping segments of sound samples, thus saving computational effort. The identification process is periodically carried out on the contents of the rolling fingerprint buffer. In the case of a small portable device, the fingerprint analysis can be carried out in the device and the results transmitted to a recognition server using a relatively low-bandwidth data channel, since the fingerprint stream is not very data-intensive. The rolling fingerprint buffer may be held on the portable device and transferred to the recognition server each time, or it may be held at the recognition server, in which case a continuing recognition session is cached on the server.

In such a rolling buffer recognition system, new sound recordings can be recognized as soon as sufficient information is available for recognition. Sufficient information may take up less than the length of the buffer. For example, if a distinctive song can be

recognized uniquely after one second of play, and the system has a one-second recognition periodicity, then the song can be recognized immediately, although the buffer may have a 15-30 second length. Conversely, if a less distinctive song requires more seconds of sample to recognize, the system must wait a longer period before declaring the identity of the song. In this sliding window recognition scheme, sounds are recognized as soon as they can be identified.

It is important to note that while the present invention has been described in the context of a fully functional recognition system and method, those skilled in the art will appreciate that the mechanism of the present invention is capable of being distributed in the form of a computer-readable medium of instructions in a variety of forms, and that the present invention applies equally regardless of the particular type of signal bearing media used to actually carry out the distribution. Examples of such computer-accessible devices include computer memory (RAM or ROM), floppy disks, and CD-ROMs, as well as transmission-type media such as digital and analog communication links.

CLAIMS

1. A method for comparing a media sample and a media file, comprising:
determining a set of sample fingerprints, each sample fingerprint characterizing a particular location within said media sample;
obtaining a set of file fingerprints, each file fingerprint characterizing at least one file location within said media file;
generating correspondences between said particular locations of said media sample and said file locations of said media file, wherein corresponding locations have equivalent fingerprints; and
identifying said media sample and said media file if a plurality of said corresponding locations are substantially linearly related.

2. A method for comparing an audio sample and an audio file, comprising:
for each of at least one audio file, computing a plurality of file fingerprints representing said audio file;
computing a plurality of sample fingerprints representing said audio sample; and
identifying said audio sample and said audio file if at least a threshold number of said file fingerprints are equivalent to said sample fingerprints;
wherein said sample fingerprints are invariant to time stretching of said audio sample.

3. A method for characterizing an audio sample, comprising:
computing a set of reproducible locations in said audio sample; and
computing a set of fingerprints characterizing said reproducible locations in said audio sample.

4. A method of characterizing an audio sample, comprising computing at least one fingerprint from a spectrogram of said audio sample, wherein said spectrogram comprises an anchor salient point and linked salient points, and wherein said fingerprint is computed from frequency coordinates of said anchor salient point and any linked salient points.

5. A method for recognizing a media sample, comprising identifying media files for which locations of a substantial plurality of equivalent features of said media files and said media sample are substantially linearly related.

6. A method for recognizing a media sample, comprising:
for each of a plurality of media files, providing a file representation of said media file;

providing a sample representation of said media sample; and
identifying at least one similar file representation among said file representations, wherein said similar file representation is similar to said sample representation, by searching said file representations, wherein said searching is performed in part in dependence on a probability of identification of said file representations.

7. A method for recognizing a media sample, comprising:
computing a set of sample fingerprints characterizing a segment of said media sample;
storing said fingerprints in a rolling buffer;
obtaining a set of matching fingerprints in a database index, each matching fingerprint characterizing at least one media file and matching at least one fingerprint in said rolling buffer;
identifying at least one media file having a plurality of matching fingerprints; and
removing at least one sample fingerprint from said rolling buffer.

8. A computer-implemented method for creating a database index of at least one audio file in a database, comprising:
computing a set of fingerprints representing features of each audio file, each fingerprint characterizing a particular location within said audio file; and
storing within a memory said fingerprints, said locations, and an identifier of each media file, wherein each corresponding fingerprint, location and identifier is associated in said memory.

9. The method of claim 1 wherein said determining step comprises computing a set of sample fingerprints.

10. The method of claim 1 wherein said determining step comprises receiving a set of sample fingerprints.

11. A method for comparing an audio sample and an audio file, comprising:
for each of at least one audio file, computing a plurality of file fingerprints representing said audio file;
computing a plurality of sample fingerprints representing said audio sample; and
identifying said audio sample and said audio file if at least a threshold number of said file fingerprints are equivalent to said sample fingerprints;
wherein each sample fingerprint is computed from a spectrogram of said audio sample according to the method of claim 4.

12. The method of claim 9 wherein said media sample is an audio sample.

13. The method of claim 9 wherein said identifying step comprises locating a diagonal line within a scatter plot of said corresponding locations.

14. The method of claim 13 wherein locating said diagonal line comprises forming differences between said corresponding locations.

15. The method of claim 14 wherein locating said diagonal line further comprises sorting said differences.

16. The method of claim 14 wherein locating said diagonal line further comprises calculating the peak of a histogram of said differences.

17. The method of claim 9 wherein said identifying step comprises computing one of a Hough transform and a Radon transform of said correspondences.

18. The method of claim 17 wherein said identifying step further comprises locating a peak of said Hough or Radon transform.

19. The method of claim 9 wherein said identifying step comprises determining whether the said number of correspondences exceeds a threshold value.

20. The method of claim 9 further comprising:
obtaining from a database index additional fingerprints characterizing file locations of additional media files;
generating additional correspondences between said particular locations of said media sample and said file locations of said additional media files, wherein corresponding locations have equivalent fingerprints; and
selecting a winning media file, wherein said winning media file has a largest plurality of substantially linearly related corresponding locations.

21. The method of claim 20 further comprising identifying media files for which a plurality of said corresponding locations are substantially linearly related and wherein said selecting step comprises selecting a winning media file from said identified media files.

22. The method of claim 21 wherein identifying said media files for which a plurality of said corresponding locations are substantially linearly related comprises searching a first subset of said additional media files.

23. The method of claim 22 wherein additional media files in said first subset have a higher probability of being identified than additional media files that are not in said first subset.

24. The method of claim 22 wherein identifying said media files for which a plurality of said corresponding locations are substantially linearly related further comprises searching a second subset of said additional media files, wherein said second subset is searched if no media files in said first subset are identified.

25. The method of claim 21, further comprising ranking said additional media files according to a probability of being identified.

26. The method of claim 25 wherein identifying said media files for which a plurality of said corresponding locations are substantially linearly related comprises searching said additional media files according to said ranking.

27. The method of claim 21 wherein identifying said media files for which a plurality of said corresponding locations are substantially linearly related comprises terminating said search at a media file having a number of said substantially linearly related corresponding locations that exceeds a predetermined threshold.

28. The method of claim 9 wherein said method is implemented in a distributed system.

29. The method of claim 28 wherein said computing step is performed in a client device, said obtaining, generating, and identifying steps are performed in a central location, and the method further comprises transmitting said sample fingerprints from said client device to said central location.

30. The method of claim 9, further comprising repeating said computing, obtaining, generating, and identifying steps for sequentially growing segments of said media sample.

31. The method of claim 9 wherein said obtaining, generating, and identifying steps are performed at periodic intervals on a rolling buffer storing said computed fingerprints.

32. The method of claim 9, further comprising obtaining said media sample, wherein said computing step and said obtaining step are performed simultaneously.

33. The method of claim 8, further comprising sorting said database index by fingerprint value.

34. The method of claim 8 or 9 wherein said particular locations of each audio file or within said media sample are computed in dependence on said audio file or media sample.

35. The method of claim 8 or 9 wherein each fingerprint represents at least one feature of said audio file or media sample near said particular location.

36. The method of claim 8 or 9 wherein said fingerprints are numerical values.

37. The method of claim 8 or 12 wherein values of said fingerprints specify a method for computing said fingerprints.

38. The method of claim 8 or 12 wherein said particular locations are timepoints within said audio file or sample.

39. The method of claim 38 wherein said timepoints occur at local maxima of spectral Lp norms of said audio file or sample.

40. The method of claim 8 or 12 wherein said fingerprints are computed from a frequency analysis of said audio file or sample.

41. The method of claim 8 or 12 wherein said fingerprints are selected from the group consisting of spectral slice fingerprints, LPC coefficients, and cepstral coefficients.

42. The method of claim 8 or 12 wherein said fingerprints are computed from a spectrogram of said audio file or sample.

43. The method of claim 42 wherein salient points of said spectrogram comprise time coordinates and frequency coordinates, and wherein said particular locations are computed from said time coordinates, and said fingerprints are computed from said frequency coordinates.

44. The method of claim 43, further comprising linking a plurality of said salient points to an anchor salient point, wherein one of said particular locations is computed from a time coordinate of said anchor salient point, and a corresponding fingerprint is computed from frequency coordinates of at least one of said linked salient points and said anchor point.

45. The method of claim 44, wherein said corresponding fingerprint is computed from a quotient between two of said frequency coordinates of said linked salient points and said anchor point, whereby said corresponding fingerprint is time-stretch invariant.

46. The method of claim 45, wherein said corresponding fingerprint is further computed from at least one time difference between said time coordinate of said anchor point and said time coordinates of said linked salient points.

47. The method of claim 46, wherein said corresponding fingerprint is further computed from a product of one of said time differences and one of said frequency coordinates of said linked salient points and said anchor point, whereby said corresponding fingerprint is time-stretch invariant.

48. The method of claim 8 or 12 wherein said particular locations and said fingerprints are computed from salient points of a multidimensional function of said audio file or sample, wherein at least one of said dimensions is a time dimension and at least one of said dimensions is a non-time dimension.

49. The method of claim 48 wherein said particular locations are computed from said time dimensions.

50. The method of claim 48 wherein said fingerprints are computed from at least one of said non-time dimensions.

51. The method of claim 11 or 48 wherein said salient points are selected from the group consisting of local maxima, local minima, and zero crossings of said multidimensional function.

52. The method of claim 8 or 12 wherein said fingerprints are time-stretch invariant.

53. The method of claim 8 or 12 wherein each fingerprint is computed from multiple timeslices of said audio file or sample.

54. The method of claim 53 wherein said multiple timeslices are offset by a variable amount of time.

55. The method of claim 54 wherein said fingerprints are computed in part from said variable amounts.

56. The method of claim 6 wherein said at least one similar file representation exceeds a threshold similarity to said sample representation.

57. The method of claim 6 wherein said identifying step comprises searching a first subset of said file representations, wherein said first subset contains file representations having a higher probability of identification than file representations that are not in said first subset.

58. The method of claim 57, further comprising searching a second subset of said file representations if said first subset does not comprise said at least one similar file representation.

59. The method of claim 6, further comprising ranking said file representations by said probability of identification, wherein said identifying step comprising searching said file representations in order of said ranking.

60. The method of claim 59, further comprising terminating said search when said at least one similar file representation is identified.

61. The method of claim 6, 23 or 25 wherein said probability of identification is computed in part in dependence on a recency of previous identification.

62. The method of claim 61 wherein a recency score of a particular file representation is increased when said particular file representation is identified.

63. The method of claim 61 wherein recency scores of said file representations are decreased at regular time intervals.

64. The method of claim 63 wherein said recency scores are decreased exponentially in time.

65. The method of claim 6 or 23 wherein said probability of identification is computed in part in dependence on a frequency of previous recognition.

66. The method of claim 2 wherein said sample fingerprints comprise quotients of frequency components of said audio sample.

67. The method of claim 2 wherein said sample fingerprints comprise products of frequency components of said audio sample and time differences between points in said audio sample.

68. The method of claim 4, 11 or 44, wherein said linked salient points fall within a target zone.

69. The method of claim 68, wherein said target zone is defined by a time range.

70. The method of claim 68, wherein said target zone is defined by a frequency range.

71. The method of claim 68, wherein said target zone is variable.

72. The method of claim 7, further comprising repeating said method for additional segments of said media sample.

73. The method of claim 7 wherein said computing, storing, and removing steps are performed in a client device and said obtaining and identifying steps are performed in a central location, and wherein the method further comprises transmitting said sample fingerprints from said client device to said central location.

74. The method of claim 7 wherein said computing step is performed in a client device and said storing, obtaining, identifying, and removing steps are performed in a central location, and wherein the method further comprises transmitting said fingerprints from said client device to said central location.

75. The method of claim 3, wherein said reproducible locations and said fingerprints are computed simultaneously.

76. A program storage device accessible by a computer, tangibly embodying a program of instructions executable by said computer to perform method steps for comparing a media sample and a media file, said method steps comprising:

computing a set of sample fingerprints, each sample fingerprint characterizing a particular location within said media sample;

obtaining a set of file fingerprints, each file fingerprint characterizing at least one file location within said media file;

generating correspondences between said particular locations of said media sample and said file locations of said media file, wherein corresponding locations have equivalent fingerprints; and

identifying said media sample and said media file if a plurality of said corresponding locations are substantially linearly related.

77. A system for recognizing a media sample, comprising:

a landmarking and fingerprinting object for computing a set of particular locations within said media sample and a set of sample fingerprints, each sample fingerprint characterizing one of said particular locations ;

a database index containing file locations and corresponding file fingerprints for at least one media file; and

an analysis object for:

locating a set of matching fingerprints in said database index, wherein said matching fingerprints are equivalent to said sample fingerprints;

generating correspondences between said particular locations of said media sample and file locations of said at least one media file, wherein corresponding locations have equivalent fingerprints; and

identifying at least one media file for which a plurality of said corresponding locations are substantially linearly related.

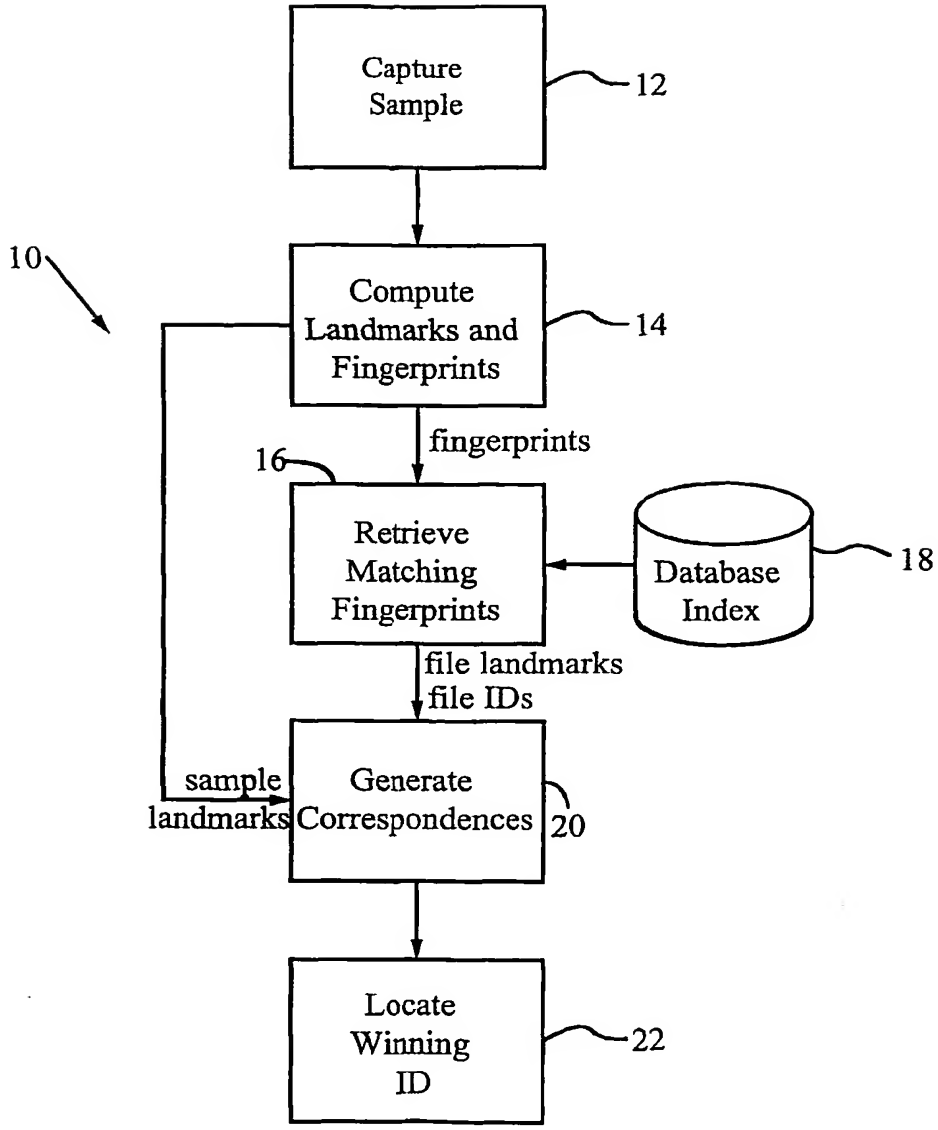
Capture Sample
12
10
Compute Landmarks and Fingerprints
14
fingerprints
16
Retrieve Matching Fingerprints
Database Index
18
file landmarks
file IDs
sample landmarks
Generate Correspondences
20
Locate Winning ID
22

FIG. 1

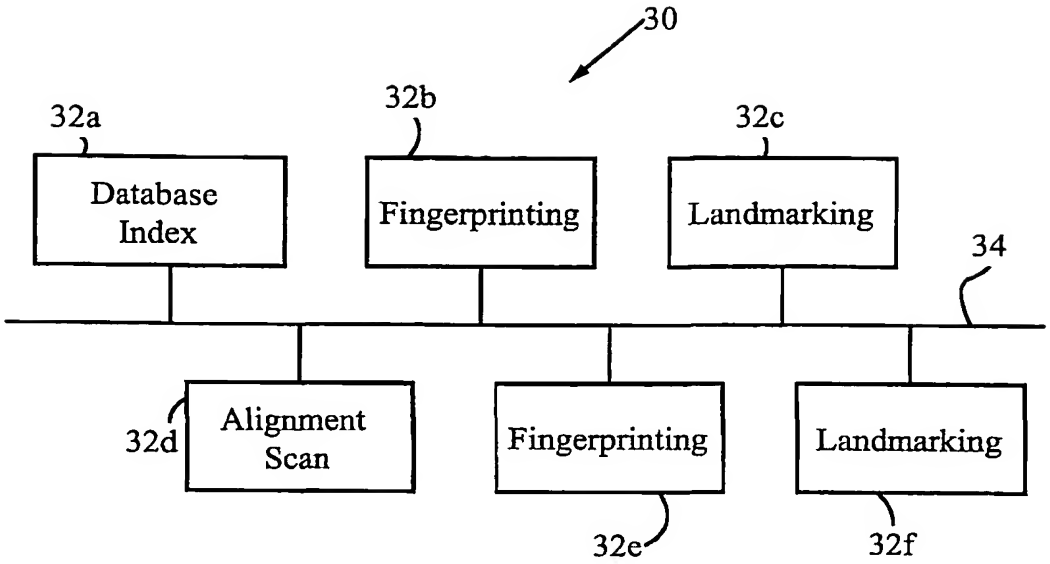
30
32a
Database Index
32b
Fingerprinting
32c
Landmarking
34
32d
Alignment Scan
Fingerprinting
32e
Landmarking
32f

FIG. 2

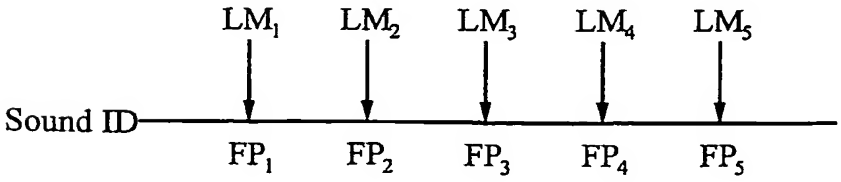
LM1
LM2
LM3
LM4
LM5
Sound ID
FP1
FP2
FP3
FP4
FP5

FIG. 4

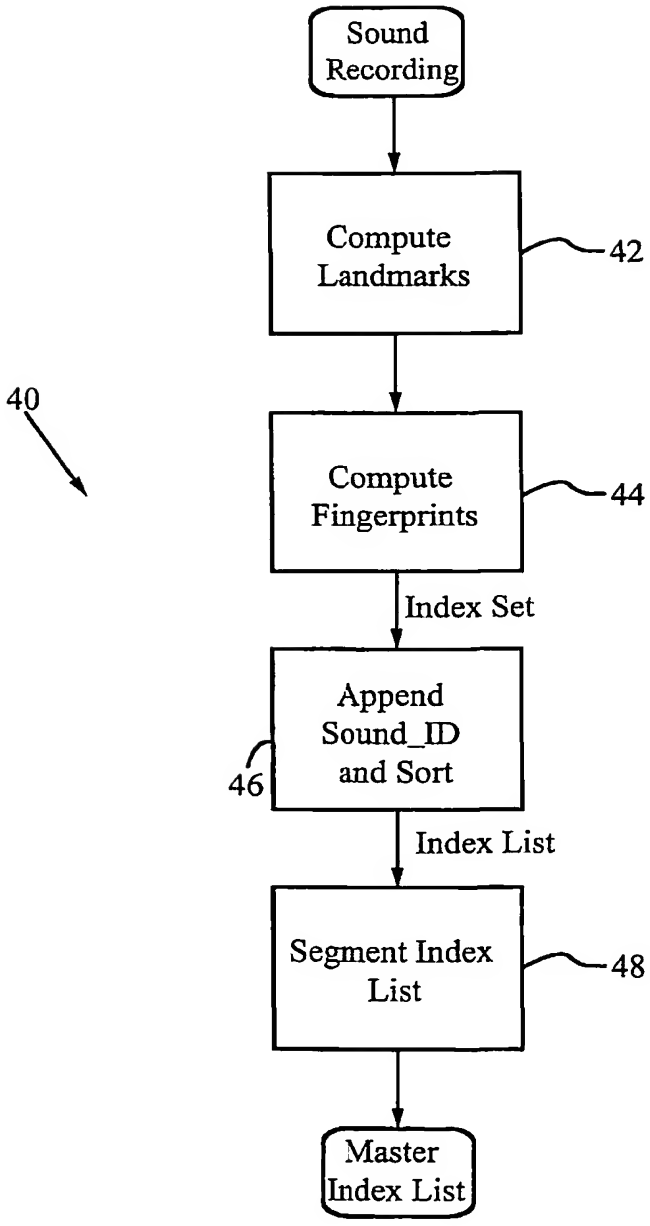
Sound Recording
Compute Landmarks
42
40
Compute Fingerprints
44
Index Set
Append Sound_ID and Sort
46
Index List
Segment Index List
48
Master Index List

FIG. 3

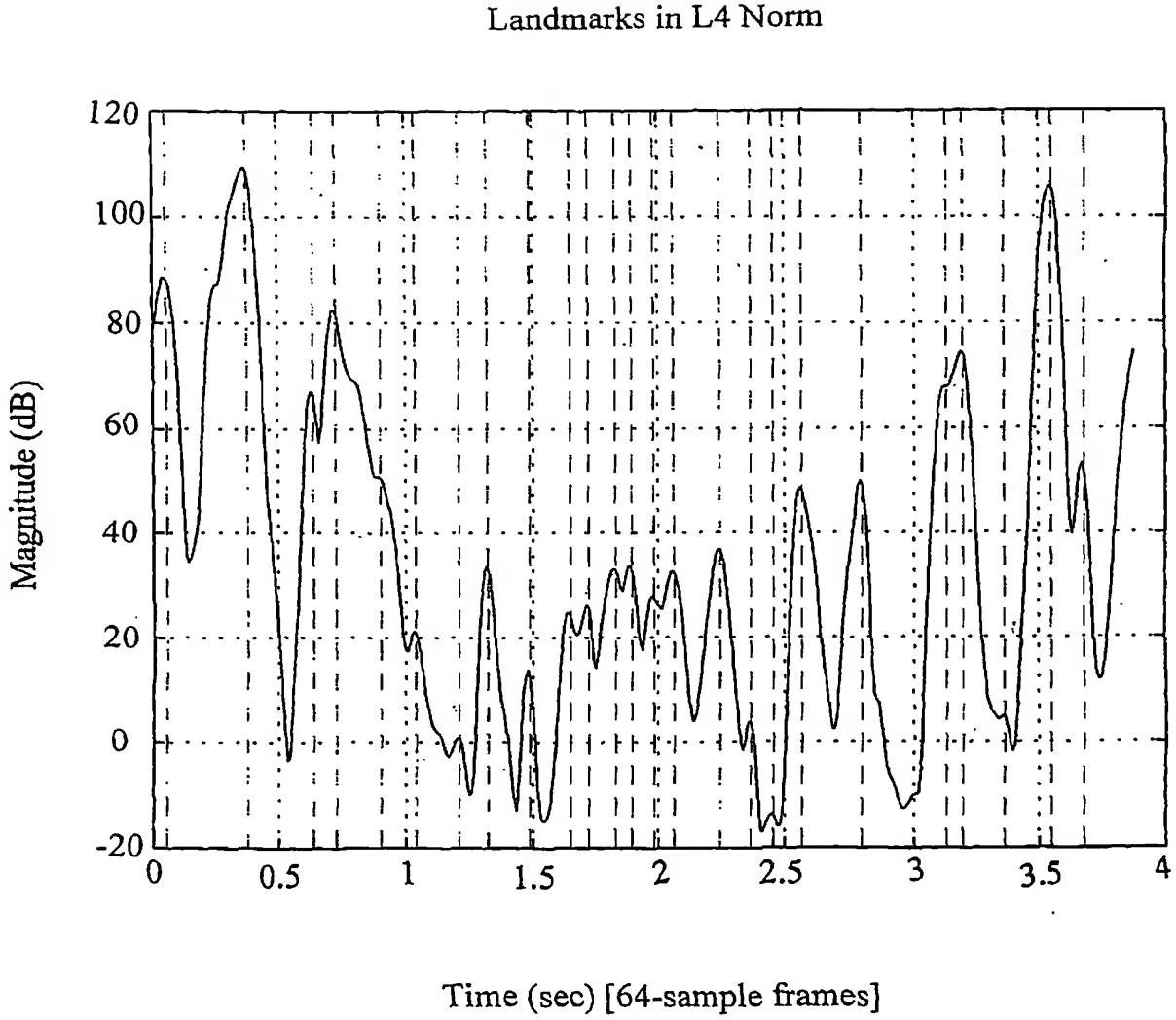
Landmarks in L4 Norm
Magnitude (dB)
120
100
80
60
40
20
0
-20
0
0.5
1
1.5
2
2.5
3
3.5
4
Time (sec) [64-sample frames]

FIG. 5

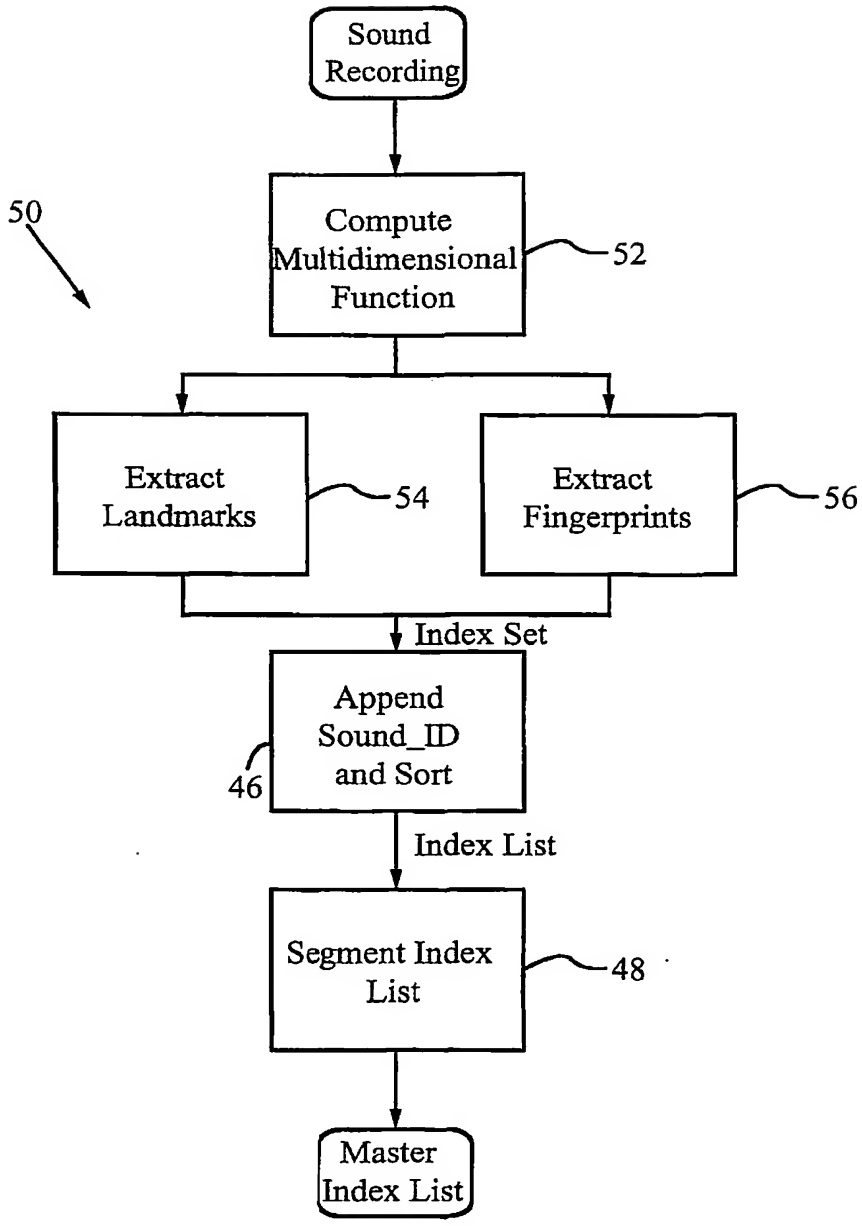
Sound Recording
50
Compute Multidimensional Function
52
Extract Landmarks
54
Extract Fingerprints
56
Index Set
Append Sound_ID and Sort
46
Index List
Segment Index List
48
Master Index List

FIG. 6

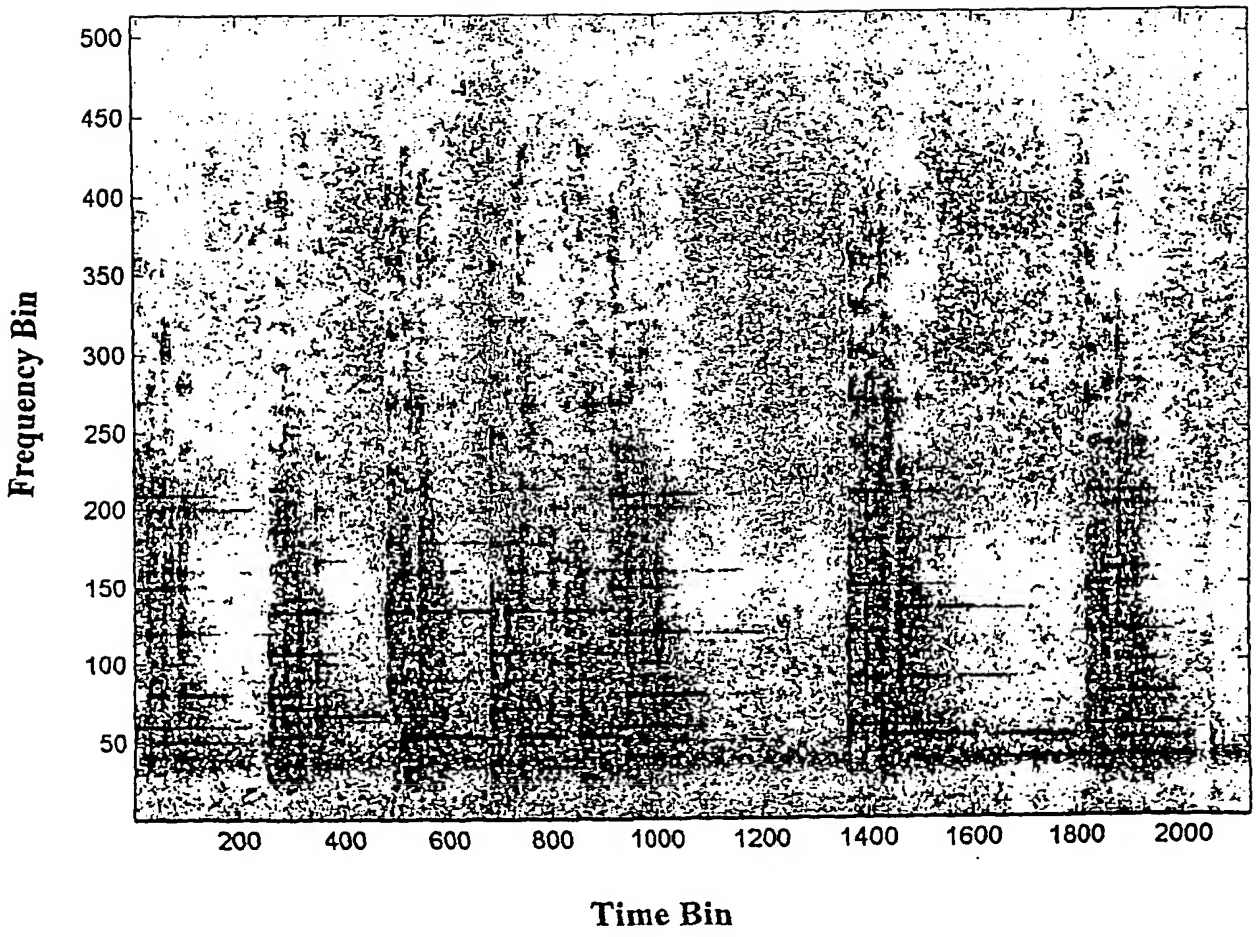
Frequency Bin
500
450
400
350
300
250
200
150
100
50
200
400
600
800
1000
1200
1400
1600
1800
2000
Time Bin

FIG. 7A

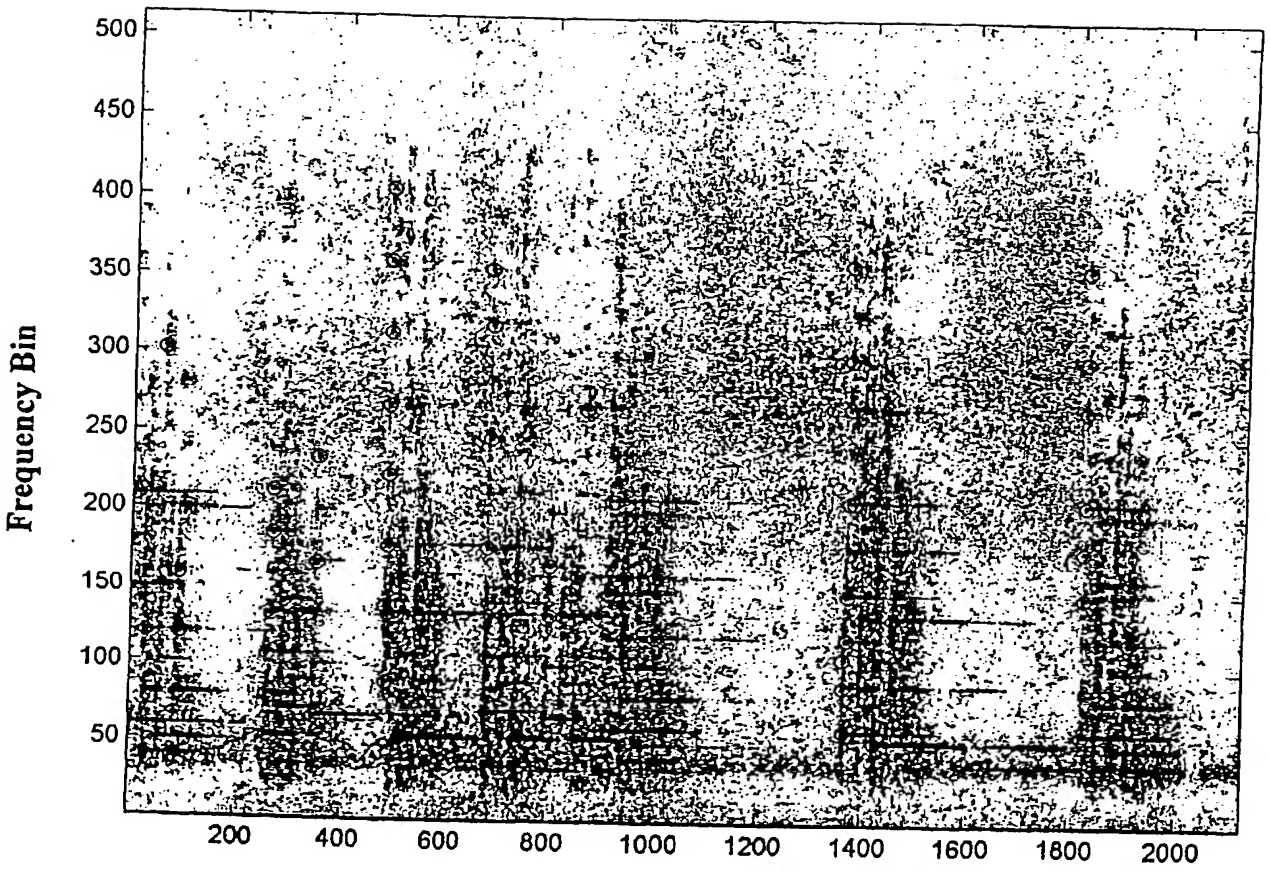
Frequency Bin
500
450
400
350
300
250
200
150
100
50
200
400
600
800
1000
1200
1400
1600
1800
2000
Time Bin

FIG. 7B

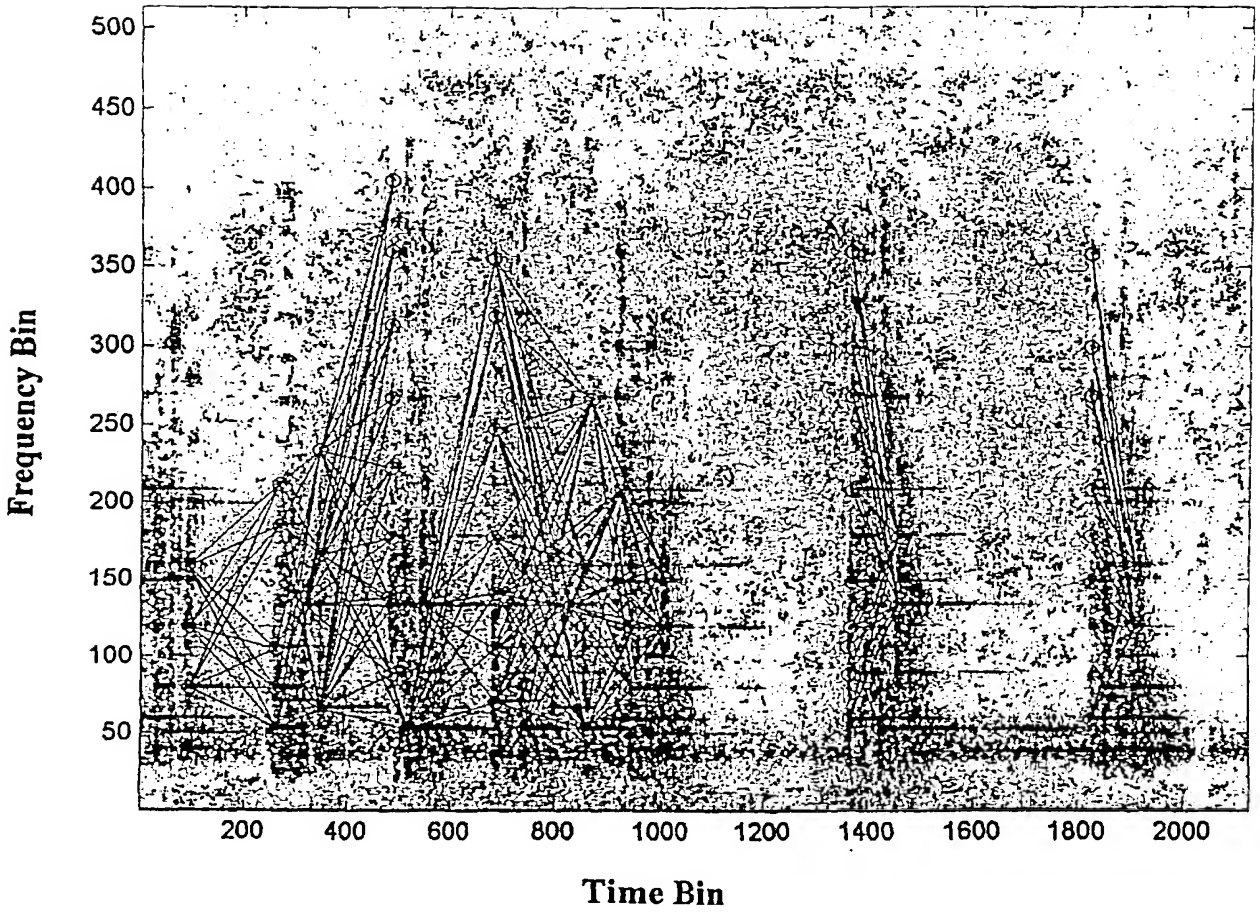
Frequency Bin
500
450
400
350
300
250
200
150
100
50
200
400
600
800
1000
1200
1400
1600
1800
2000
Time Bin

FIG. 7C

Index Sets

$$\begin{bmatrix} \text{Sound_ID}_1 \\ (\text{fingerprint}_1, \text{landmark}_1) \\ (\text{fingerprint}_2, \text{landmark}_2) \\ \vdots \\ (\text{fingerprint}_m, \text{landmark}_m) \end{bmatrix} \quad \cdots \quad \begin{bmatrix} \text{Sound_ID}_n \\ (\text{fingerprint}_p, \text{landmark}_p) \\ (\text{fingerprint}_{p+1}, \text{landmark}_{p+1}) \\ \vdots \\ (\text{fingerprint}_t, \text{landmark}_t) \end{bmatrix}$$

FIG. 8A

Index List

$$\begin{bmatrix} (\text{fingerprint}_1, \text{landmark}_1, \text{sound_ID}_1) \\ (\text{fingerprint}_2, \text{landmark}_2, \text{sound_ID}_1) \\ \vdots \\ (\text{fingerprint}_m, \text{landmark}_m, \text{sound_ID}_1) \\ \vdots \\ (\text{fingerprint}_p, \text{landmark}_p, \text{sound_ID}_n) \\ (\text{fingerprint}_{p+1}, \text{landmark}_{p+1}, \text{sound_ID}_n) \\ \vdots \\ (\text{fingerprint}_t, \text{landmark}_t, \text{sound_ID}_n) \end{bmatrix}$$

FIG. 8B

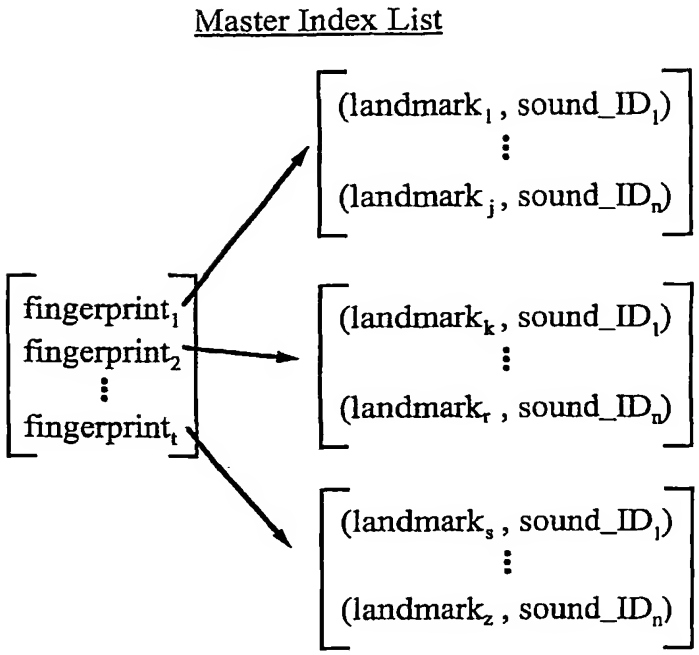
Master Index List
(landmark$_1$, sound_ID$_1$)
(landmark$_j$, sound_ID$_n$)
fingerprint$_1$
fingerprint$_2$
fingerprint$_t$
(landmark$_k$, sound_ID$_1$)
(landmark$_r$, sound_ID$_n$)
(landmark$_s$, sound_ID$_1$)
(landmark$_z$, sound_ID$_n$)

FIG. 8C

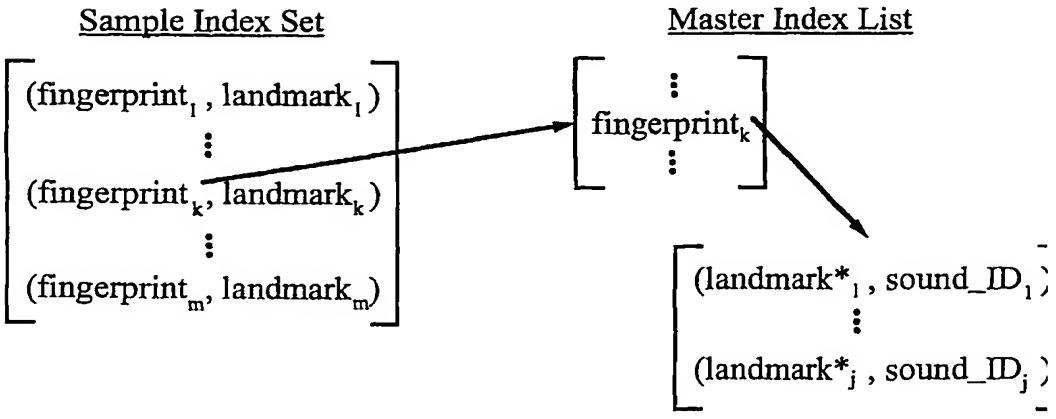
Sample Index Set
(fingerprint$_1$, landmark$_1$)
(fingerprint$_k$, landmark$_k$)
(fingerprint$_m$, landmark$_m$)
Master Index List
fingerprint$_k$
(landmark*$_1$, sound_ID$_1$)
(landmark*$_j$, sound_ID$_j$)

FIG. 9A

Candidate List

$$\begin{bmatrix} (\text{landmark}_1, \text{landmark*}_1, \text{sound_ID}_1) \\ \vdots \\ (\text{landmark}_k, \text{landmark*}_j, \text{sound_ID}_j) \\ \vdots \\ (\text{landmark}_m, \text{landmark*}_r, \text{sound_ID}_n) \end{bmatrix}$$

FIG. 9B

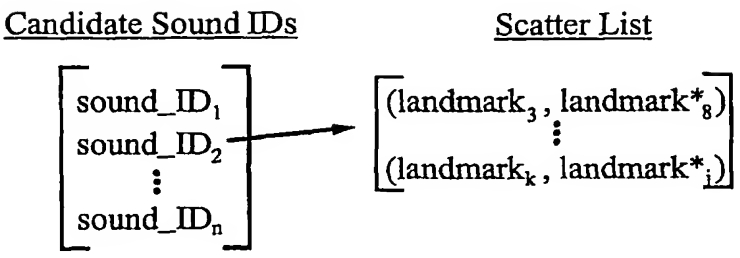

FIG. 9C

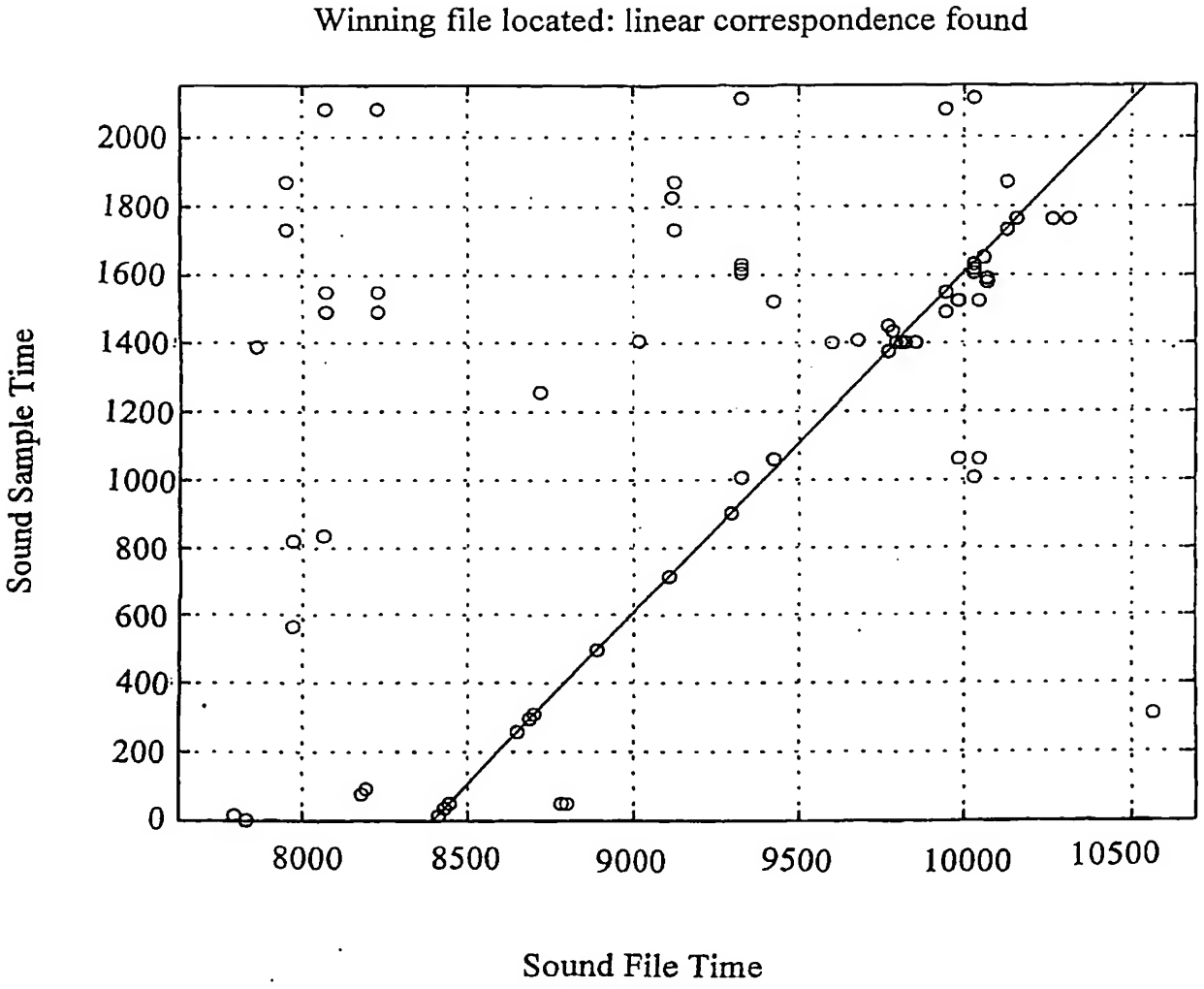
Winning file located: linear correspondence found
Sound Sample Time
2000
1800
1600
1400
1200
1000
800
600
400
200
0
8000
8500
9000
9500
10000
10500
Sound File Time

FIG. 10A

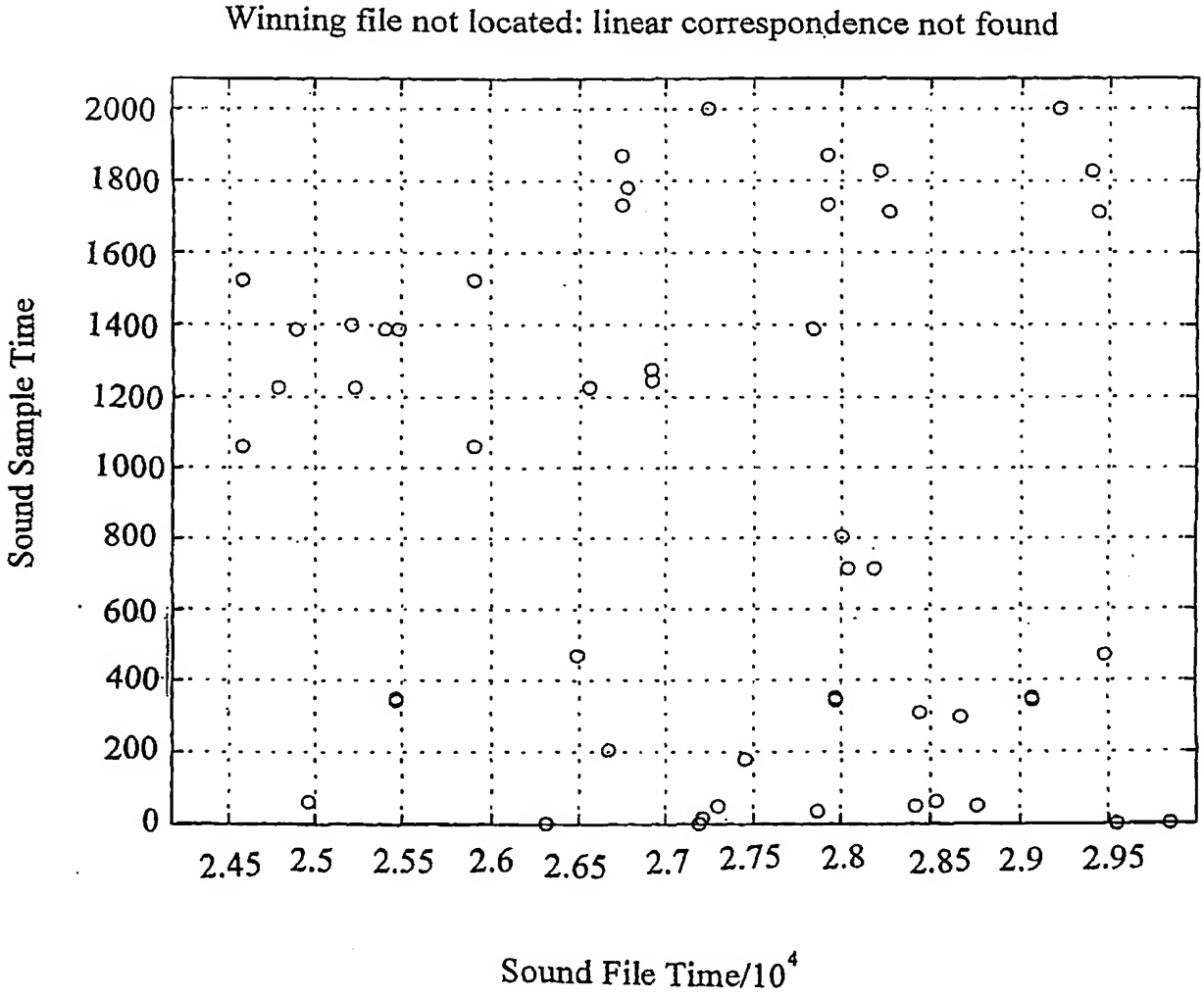
Winning file not located: linear correspondence not found
Sound Sample Time
2000
1800
1600
1400
1200
1000
800
600
400
200
0
2.45
2.5
2.55
2.6
2.65
2.7
2.75
2.8
2.85
2.9
2.95
Sound File Time/10^4

FIG. 10B